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FABRIC PATTERN RECOGNITION USING IMAGE PROCESSING AND AHP METHOD

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Abstract:

This article aims to provide methods and a system to recognize the woven fabric patterns automatically. Two different approaches were designed to identify the woven patterns in this article: image analysis and the analytic hierarchy process (AHP). In this work, identifying the woven fabric patterns is based on the measurement of some characteristics and parameters that clearly describe and explain the contexture of the fabric. The methods used were essentially pattern recognition and image processing, which aim to numerically calculate four critical parameters which can give a clear idea of the texture and the patterns of fabrics: the continuity of diagonal lines, the section succession in the vertical direction, section succession in the horizontal direction, and isolated blocks. Then, we used the AHP to classify basic weave patterns into three classes representing the fundamental weaves: plain, twill, and satin. Finally, the statistical approach used to evaluate the efficiency of the proposed method concerning classification showed high correlation values between the predicted results and the experimental values. This study has practical implications in the textile industry, especially in the clothing sector. The manufacturers can use the results to automatically identify the woven fabric patterns without using the manual examination method.

Keywords:

image processing, pattern recognition, fabric pattern, AHP, textile analysis

1. Introduction

The conventional means of pattern identification require manual operations, which are time-consuming and easily strain the operator's eyes [1]. Consequently, it is interesting to develop a computerized method for recognizing and identifying the weaves of the fabric. Furthermore, typical methods call for manual operations with simple tools based on visual inspection by the operator to examine and identify the pattern structure [2]. Thus, generating image processing and programed data investigation procedures would be interesting in determining the fabric's features [3].

Classification and identification are different problems in fabric pattern recognition; classification involves dividing into classes and separating into groups according to some common attributes, while identification involves identifying and determining the name or characteristics of one item. In the case of recognizing fabric weaves, classification makes it possible to group the tested weaves according to the classes of the fundamental weaves. However, pattern identification is much more precise and complicated because we must determine each sample's name and structural characteristics.

Image processing consists of eliminating parasitic information and storing the relevant information for pattern recognition [4]. Image processing techniques were mainly employed for fabric pattern identification [5]. Many researchers have exploited the advantages of artificial intelligence to solve the problem of recognizing the weaves of fabrics [6]. They combined image processing techniques and artificial intelligence methods. Among the methods used, some researchers combined image processing techniques with a neural network to solve the problem [7]. They worked on developing an efficient system that minimizes the number of inputs in the architecture of neural networks.

In other studies, researchers used the warp and weft floats to determine weave patterns [8] or the fast Fourier transform techniques [9]. Advanced methods like KFCM and IDM have been carefully used to identify the fabric pattern and repetition for yarn-dyed fabrics [10]. Also, we mention the gradient histogram among the tools developed in image processing and used in recognizing the woven fabric pattern [11]. Image processing has proven to be an effective method for analyzing fabric structures and identifying types of patterns. In their study, Zheng et al. presented a new way to recognize yarn-dyed fabrics with distorted repeat patterns using multi-scale density [12].

In the study of Huang et al. [13], a new approach based on the digital processing of the fabric was used. It consists of capturing the images with a maximum resolution. Next, the images were archived to be manipulated and processed with algorithms that provide measurable parameters. Then, the neural networks and image transformation technology were presented to classify the fabric weaves. In another study [14], an autocorrelation function was employed to define the fabric pattern ratio. In this work, the displayed image of the fabrics was obtained and treated automatically to achieve excellent results. The results demonstrated that three types of basic weaves could be classified with precision, and the parameters of the yarn count, such as weft count and blending, could also be obtained. Other researchers have also used optical coherence tomography (OCT) to recognize fabric weave patterns [15].

Furthermore, advanced methods like learning vector quantization have automatically allocated the woven fabric structure [16]. In addition, several researchers have worked on the systematic discovery of construction characteristics of yarn-dyed fabric [17,18]. Some others presented an original mutated genetic and imperialist rival algorithm for composition determination of woven fabric images [19].

In image analysis, the conversion stage from a color image to a grayscale image directly influences the time and speed of data processing. Also, histogram equalization aims to assign the pixels' intensity values to obtain a more uniform distribution in the gray level and enhance the image's visual presentation [20]. Kang et al. developed an automatic fabric assessment system to analyze the fabric structure and objectively assess the quality automatically. First, the images were filtered by Gaussian filtering and histogram equalization. Then, several fabric building parameters were measured by programs based on image processing [21].

In recent years, image analysis has significantly enhanced the capabilities of woven fabric pattern recognition processing [22]. Iqbal Hussain et al. [23] also contributed to this cause, showing that deep convolutional neural networks could be employed for both the recognition and classification of woven fabrics.

Sun et al. [24] identified the potential of spectroscopy-based pattern recognition methods for classifying textile fabrics and found them adequate for fabric analysis. Anila et al. [25] examined fabric texture analysis and weave pattern recognition through intelligent processing methods and concluded that advanced technologies might be useful in textile evaluation.

New ideas in structural textile pattern recognition and processing using hypergraphs were presented to improve methods of textile analysis [26]. In parallel, color pattern recognition for yarn-dyed fabrics contributed to the knowledge of textile classification techniques [27]. Moreover, Guo et al. [28] designed an automatic recognition method to determine the repeat size of weave patterns in woven fabric images, which significantly advances fabric analysis techniques.

A notable innovation introduced a video-based automatic fabric pattern recognition system with a Bayesian-optimized convolutional neural network to enhance the efficiency of fabric analysis [29]. In addition, using multi-layer extraction techniques to identify complex patterns in fabric enhanced the pattern recognition capability [30]. Pattern driven color pattern recognition methods that enhance the design process of printed fabric motifs were also explored by Zheng [31] in order to contribute to advancements in textile design methodologies. Meng et al. [32] developed a multi-task, multi-scale convolutional neural network to enhance the accuracy of fabric analysis for the automatic recognition of woven fabric patterns. Xiao et al. [33] also developed a transform invariant low-rank textures technology-based automatic recognition system for woven fabric patterns to increase the precision and efficiency of fabric pattern analysis. Finally, Sabuncu and Özdemir applied OCT to recognize fabric weave patterns. They discussed fundamental techniques of fabric weave identification, as well as automated methods for checked and colored fabrics, with a focus on striped and colored fabrics, to show the versatility of OCT in textile analysis [34–36].

In this article, we used digital image analysis to evaluate the specific characteristics of fabric construction. We began with a series of image processing steps and progressed to a stage of information extraction on the fabric texture. After that, we opted to use the analytic hierarchy process (AHP). Generally, the main problems of pattern recognition are the description of the input data and the extraction of characteristics of these patterns that are applied to decrease the difficulty.

Based on the analysis of the current research and the previous works, we can obtain some key differences between our study and others in the literature. First, our study combines two distinct methods – image analysis and AHP – to recognize the woven fabric patterns. Most other studies focus on a single method: deep learning, image processing, or specific algorithms. We introduced four critical parameters – continuity of diagonal lines (CDL), section succession in the vertical/horizontal directions (SSV/SSH), and isolated blocks (IBL) – to quantitatively describe the fabric's texture and pattern. At the same time, most other studies do not emphasize this specific combination of measured parameters.

Additionally, we used a statistical method to assess how well our method was performing, and we found a perfect correlation between our predictions and experimental results. This study was also extended to practical applications in the textile industry, especially for manufacturers who want to implement an automated solution to identify woven fabric patterns. Although some studies may discuss applications, focusing on the practicality and the direct benefits to the clothing sector makes our approach different.

Our study is distinct in that we attempted to develop an automatic recognition system with analytical and hierarchical methods, which is not usual in the literature. These differences describe the innovative parts of our research and their contribution to the woven fabric pattern recognition field.

2. Materials and methods

2.1. Materials

In this work, we used 72 fabric samples. This database has different types of weaves (plain, twill, and satin). The samples presented have different basic structural parameters, such as the yarn count and the thickness of the fabric. Table 1 gives an idea of the range of values of these criteria for the patterns tested. These parameters are essential in the problem of pattern classification. However, our study is the first that highlights the determination by an image analysis process.

Table 1. Statistical data of structural parameters

	Number of warp yarns/cm			Number of weft yarns/cm			Thickness (mm)		
	Max	**Min**	**Average**	**Max**	**Min**	**Average**	**Max**	**Min**	**Average**
Plain	40	12	21.12	32	10	18.08	0.71	0.48	0.60
Twill	38	14	24.71	30	10	20.06	0.72	0.45	0.57
Satin	40	17	25.46	36	14	20.20	0.70	0.46	0.56

In Figure 1, we present some samples of the weaves of the fabric studied in our work. First, the fabrics were captured with adequate resolution to be processed effectively later. The method consists of putting the tested sample in a scanner while ensuring the warp and weft yarns are parallel to the device's edges.

Then, the digital data were transferred to a computer program developed under MATLAB. The main objective of this part was to analyze the images and calculate the digital characteristics.

In this figure, we have presented the three basic patterns of fabrics. Our primary goal in all the rest of the work was to identify these fabrics automatically. To separate and easily classify them, we tried to find measurable values for each type of fabric. So, we have listed their main characteristics as follows.

- An alternating and consecutive crossing between the warp and weft yarns characterizes plain weaves.
- Twill weaves are identified and characterized primarily by diagonal lines either in the right or left direction.
- The importance of the concept of floating yarns recognizes satin weaves.

2.2. Experimental method for determining the weave of a fabric

The NFG 07-154 standard, which applies to all fabrics, aims to determine the weave ratio, hence determining the crossing of the warp and weft yarns. The weave ratio represented on the weave paper is retained to represent the weaves of the fabric. Care was taken to arrange different yarns of the weave when there is more than one thread of warp or weft. The tools required to apply this standard method were weave paper, a low-power magnifying glass, tweezers, scissors, and an unwinding needle.

2.3. Presentation of the analysis of variance (ANOVA) method

ANOVA is a method and approach based on statistical and mathematical principles. It classifies the obtained variance data into various components for interpretation. A one-way ANOVA is used for three or more data groups to determine the relationship between the dependent and independent variables.

An ANOVA test is a process that determines if examination or experimental results are significant. In other words, they assist in making the best decision to decline the null hypothesis or allow the alternate hypothesis. In addition, it is a system for testing groups and confirming if there is a distinction between them.

The resulting numerical data are processed to validate the ANOVA calculations, and the critical P and F values are verified using a comparative study.

2.4. AHP

AHP is a system for classifying and interpreting complex judgments by practicing math and psychology.

We present below the different calculation steps:

Step 1: Begin the AHP by determining the alternatives that are required to be judged.

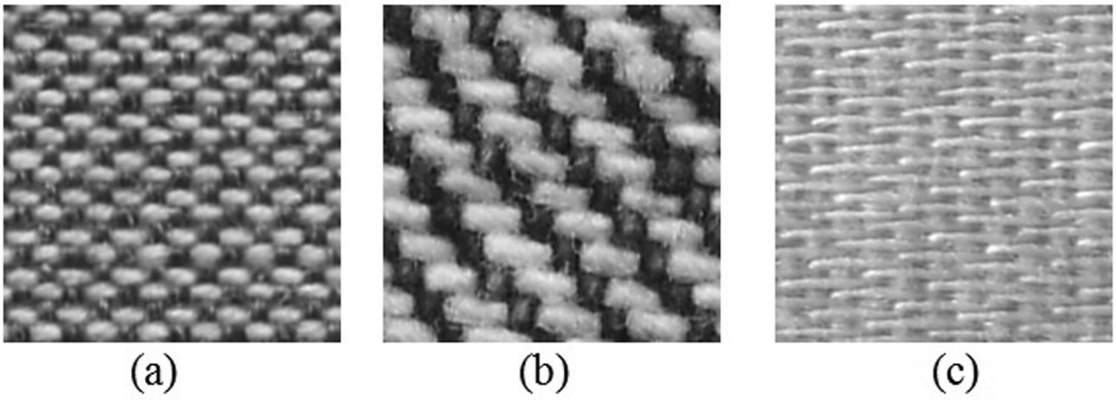

Figure 1. Presentation of the basic pattern. (a) Plain weave, (b) Twill weave, and (c) satin Weave.

Step 2: Establish the problem and criteria.

Step 3: Set priority among criteria applying pairwise comparison.

Step 4: Verify consistency.

Step 5: Take the relevant weights.

3. Results and discussion

3.1. Image processing operation

This study aims to achieve clear images that can be quickly processed for effective results. Starting from an original image containing all digital information, we wanted to obtain binary images which were easy to process and manipulate without losing valuable data.

The process adopted in analyzing the fabric image can be summarized in several steps. First, image acquisition is implemented to get the original image using appropriate imaging technologies to ensure that all the necessary digital information is included. Then, the image is preprocessed to reduce noise, adjust the contrast, and normalize it to prepare it for further analysis. After that, for segmentation, the featured image of interest is divided into different images of the region based on relation thresholding to edge the detection background.

After that, we pass to a binary image in which the value of each pixel is either 0 (which represents the background) or 1 (which represents the foreground). This simplification is helpful for faster processing and analysis. The binary image analysis tries to recognize and extract important features such as shape and size.

In the last part of treatments, algorithms are used to develop judgments established on the extracted features and characteristics to make decisions.

This systematic approach generally improves the quality of processed images and guarantees that helpful information is preserved for analysis and decision-making.

3.2. Determination of measurable variables

We subsequently present some measurable parameters using image processing techniques. These characteristics were used in this study as inputs in optimization and decision-support systems.

3.2.1. Rate of CDL

CDL is defined as the rate of pixels having the same intensity in the same diagonal direction compared to the total number of pixels in this direction (Figure 2). Then, we calculated the average of all the values of the ratios found.

The rate of CDL was calculated using the following formula:

$$\mathrm{CDL} = \frac{1}{K} \times \sum_{i=1}^{K} \frac{\mathrm{Max}(x_{1i}, x_{2i}, \ldots, x_{ji})}{N_i} \times 100, \tag{1}$$

with K being the total number of adjacent diagonal lines in an image and N_i the total number of pixels in the ith diagonal line.

Each ith diagonal line was divided into j sections of pixels; each nth section (n: 1, 2, …, j) is characterized by a set of adjacent pixels of the same value (0 or 1). The number of pixels was symbolized by x_{ni}.

3.2.2. Rate of SSV

As shown in Figure 3, we defined N as the number of vertical lines. Each vertical line was denoted by n, with n = 1. N: we divided each nth vertical line into several sections. Each section was defined as the existence of an adjacent series of black pixels and a series of white pixels. Each section was symbolized by $S_{n,i}$ with i = 1. K: it is the total number of sections in each vertical line. We also defined $X_{\mathrm{B},n,i}$ as the total number of black pixels in the ith section in the nth vertical line and $X_{\mathrm{W},n,i}$ is the total number of white pixels in the ith section in the nth vertical line.

The rate of SSV was calculated using the following formula:

$$\mathrm{SSV} = \frac{1}{N} \times \left(\sum_{n=1}^{N} \left(\frac{1}{K} \times \sum_{i=1}^{K} \frac{\mathrm{Min}(X_{\mathrm{B},n,i}, X_{\mathrm{W},n,i})}{\mathrm{Max}(X_{\mathrm{B},n,i}, X_{\mathrm{W},n,i})} \right) \right) \times 100. \tag{2}$$

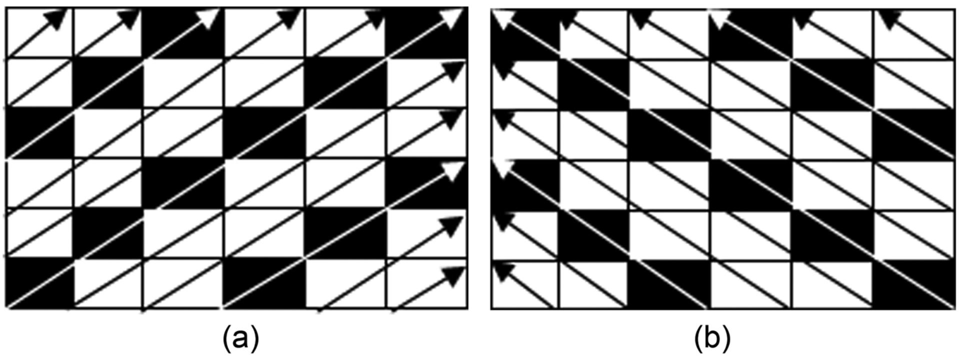

Figure 2. Schematic representation of diagonal lines in an image. (a) Diagonal line slanting to the right and (b) Diagonal line slanting to the left.

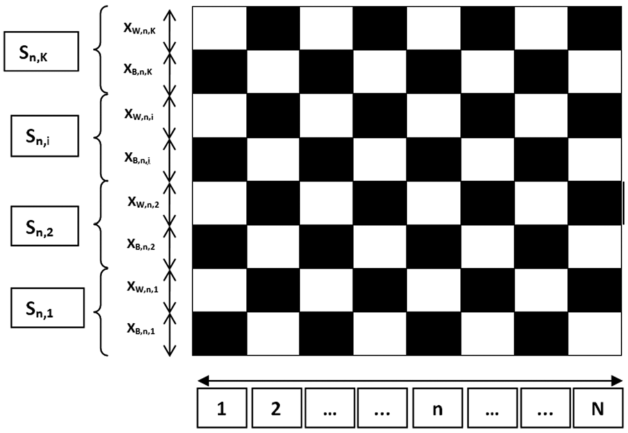

Figure 3. Schematic presentation of SSV.

3.2.3. Rate of SSH

As shown in Figure 4, the rate of SSH was calculated in the same way as the previous SSH parameter but with a reversal in the directions. It was calculated using the following formula:

$$SSH = \frac{1}{M} \times \left(\sum_{m=1}^{M} \left(\frac{1}{H} \times \sum_{j=1}^{H} \frac{\mathrm{Min}(X_{B,m,j}, X_{W,m,j})}{\mathrm{Max}(X_{B,m,j}, X_{W,m,j})} \right) \right) \times 100, \qquad (3)$$

with M being the number of horizontal lines, H the number of sections in one horizontal direction, $S_{m,j}$ the reference of the jth section in the mth horizontal direction (m: 1…M; j: 1…H), $X_{B,m,j}$ the total number of black pixels in the jth section in the mth horizontal line, and $X_{W,m,j}$ the total number of white pixels in the jth section in the mth horizontal line.

3.2.4. Rate of IBL

A block of similarly isolated pixels was defined as a set of adjacent pixels with the same value (0 or 1) and surrounded by other pixels with different values in all the possible directions, as shown in Figure 5.

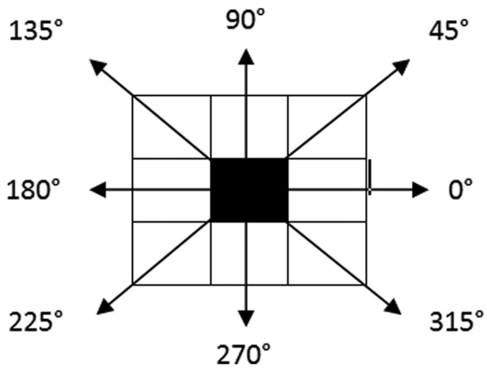

Figure 5. Presentation of all the possible directions of a pixel.

For example, if we designate the blocks using a set of black pixels, we look for the blocks surrounded by white pixels, as shown in Figure 6.

We carried out our calculations on an image of dimensions $N \times M$. The rate of IBL was calculated using the following formula:

$$IBL = \mathrm{Max}\left(\frac{NB_{white}}{NP_{white}}, \quad \frac{NB_{black}}{NP_{black}} \right) \times 100, \qquad (4)$$

with NB_{white} being the number of white pixel blocks, NB_{black} the number of black pixel blocks, NP_{white} the total number of black pixels in the whole image, and NP_{black} the total number of black pixels in the entire image.

3.3. Presentation of numerical values for processed images

We used the previously mentioned image parameter definitions. Next, we applied our sample database to determine the fabric's weave properties. Finally, we have provided a statistical analysis in Table 2 to explain the process better.

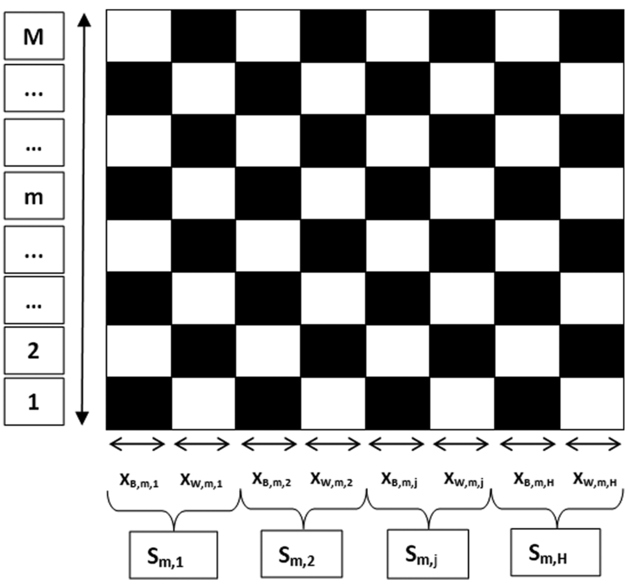

Figure 4. Schematic presentation of SSH.

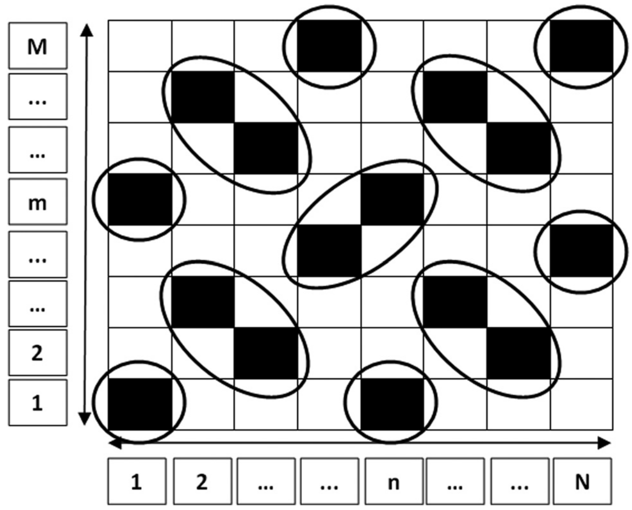

Figure 6. Schematic presentation of IBL.

Table 2. Statistical data of image parameters

Image features	Minimum	Average	Maximum	Standard deviation	Variance
CDL	5	29.37	60	18.32	335.81
SSV	4	28.30	70	20.37	415.28
SSH	12	34.86	69	16.68	278.23
IBL	10	23.01	60	13.30	176.91

Table 3. A study case of fabric characteristics

CDL	SSV	SSH	IBL
14	35	43	15

3.4. Using the AHP to pattern recognition

We used the AHP in our research to determine the suitable fabric pattern. For this, we started to specify the AHP for the following classification: fabric image parameters (CDL, SSV, SSH, and IBL) and fabric patterns (plain, twill, and satin).

This system has four inputs representing the image characteristics (CDL, SSV, SSH, and IBL) and three outputs related to fabric patterns (plain, twill, and satin). To explain the calculation process and determine the correct class of fabric pattern by the AHP, a case study of an image of one fabric-defined characteristic is presented in Table 3. Then, through this calculation we tried to determine the corresponding fabric pattern.

In Table 4, we have presented the pairwise comparison matrix between the criteria. Then, we have displayed the normalization matrix in Table 5. After that, we calculated the consistency ratio (CR), as shown in Table 6.

Table 4. Pairwise comparison matrix of criteria

	CDL	SSV	SSH	IBL
CDL	1	1/3	1/3	1/2
SSV	3	1	1/2	3
SSH	3	2	1	3
IBL	2	1/3	1/3	1
Sum	9.00	3.67	2.17	7.50

Following a complete mathematical approach, we proceeded to finalize and validate the AHP results. The most crucial criticism we seek to determine is the CR:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}, \tag{5}$$

where RI is the random index (Table 7) and CI is the consistency index, which was calculated through the following equation

$$\mathrm{CI} = \frac{\gamma_{\max} - n}{n - 1}, \tag{6}$$

where n is the order of the matrix and $\gamma_{\max}$ is the average of all the consistency values.

3.4.1. Obtaining an overall relative score for each alternative

To validate the calculation, we calculated each pairwise comparison matrix's CR. To explain the procedure adopted, we presented above the pairwise comparison matrix for each class of fabric pattern for the criterion: the CDL (Table 8), the normalization matrix (Table 9), and CR calculation (Table 10).

We continued determining the pairwise comparison matrix for each fabric pattern class for the other criteria (SSV, SSH, and IBL). Finally, we obtained the optimal result (pattern fabric) through the solution matrix (Table 11).

Table 6. Consistency ratio for Input parameters

RI	**0.90**
n	4
$\gamma_{\max}$	4.12
CI	0.04
CR	0.05

Table 5. Normalization matrix

	CDL	SSV	SSH	IBL	Weight (%)	Consistency
CDL	0.11	0.09	0.15	0.07	**0.11**	4.1
SSV	0.33	0.27	0.23	0.40	**0.31**	4.2
SSH	0.33	0.55	0.46	0.40	**0.44**	4.2
IBL	0.22	0.09	0.15	0.13	**0.15**	4.1

Table 7. Random index (RI)

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Table 8. Pairwise comparison matrix for each class of fabric pattern for the CDL criterion

	Plain weave	Twill weave	Satin weave
Plain weave	1	1/5	2
Twill weave	5	1	7
Satin weave	1/2	1/7	1
Sum	6.50	1.34	10.00

Table 9. Normalization matrix

	Plain weave	Twill weave	Satin weave	Weight (%)	Consistency
Plain weave	0.15	0.15	0.20	0.17	3.01
Twill weave	0.77	0.74	0.70	0.74	3.03
Satin weave	0.08	0.11	0.10	0.09	3.00

As shown in Table 11, it is clear that the higher weight (54%) corresponds to the pattern fabric class: plain weaves. Therefore, this AHP calculation approach was applied to all the samples.

4. Evaluation of the results

4.1. Study of the effectiveness of the method used

By comparing the results found by the AHP and the results determined experimentally, as shown in Figure 7, we see a perfect correlation between the two processes. To analyze the results found numerically, we adopted the following values in the rest of our work: plain (1), satin (2), and twill (3).

Table 10. Consistency ratio for Output parameters

RI	0.58
n	3
γ_{max}	3.01
CI	0.01
Ratio	0.01

Table 11. Matrix of solution

	CDL	SSV	SSH	IBL	Result
Plain weave	0.17	0.59	0.22	0.75	0.54
Twill weave	0.74	0.16	0.10	0.07	0.18
Satin weave	0.09	0.25	0.68	0.18	0.28

In general, the coefficient of determination (R^2) is a statistical measure that verifies the reliability of a processed method. In our case and as shown in Figure 7, R^2 equals 0.948. Therefore, this value is very close to 1. These results indicate the excellent correlation between the values found experimentally and those determined by the AHP. To better analyze the impact, we proposed adding a step of calculation of some statistical parameters, which can inform us more straightforwardly the correlation between the results. The values are mentioned in Table 12. Among these data, we can cite the following parameters:

R: correlation coefficient,

MAPE: mean absolute percent error,

MSE: mean squared error, and

RMSE: root mean squared error.

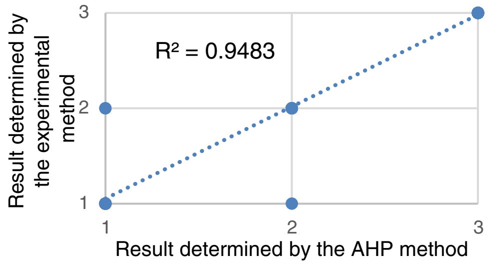

Figure 7. Correlation between the AHP and the experimental method.

Table 12. Statistical analysis of the correlation between the manual method and AHP

R	MAPE	MSE	RMSE
0.973	3.472	0.041	0.204

By analyzing the statistical data in Table 12, we observed that the value of the correlation coefficient ($R = 0.973$) was very high; it was very close to 1. This result allowed us to conclude a strong correlation between the values determined experimentally and those calculated by the AHP. Also, we found that the value of MAPE was well below 10% (MAPE = 3.47%), making it possible to conclude the excellent correlation. On the other hand, we noticed that the values of MSE and RMSE were very low (MSE = 0.041; RMSE = 0.204). These parameters measure how accurately the model predicts the response.

4.2. Study of the digital characteristics of images by the ANOVA method

Our study gave much importance to finding reliable image characteristics that digitally and perfectly describe the fabric's weave. Therefore, we planned to use the following ANOVA, which makes it possible to determine whether there were any statistically significant differences between the means of the groups (fabric patterns). This stage is critical to verify the effectiveness of these parameters in classifying and diversifying pattern fabrics (plain, twill, and satin). For this, we chose the parameter "CDL" as a calculated variable.

In ANOVA, null hypothesis means that there is no difference among group means. However, if any group differs significantly from the overall group mean, then the ANOVA will report a statistically significant result. Table 13 provides a detailed report on the statistical data for the three fabric patterns we wanted to define and classify automatically.

In Table 14, we applied the ANOVA method to determine both the probability (p-value) and the critical value for F. Using the p-value in the ANOVA output allowed us to choose whether the differences between some of the means are statistically significant. Analyzing the critical value for F can also reject or maintain the null hypothesis.

From this table, we assumed that the p-value was smaller than the designated threshold value (5%). In our case, $p = 9.25 \times 10^{-31}$. Also, the F value in our test was more significant than the F critical value (221.56 > 3.12). This result allowed us to conclude it was necessary to reject the null hypothesis. This result was very encouraging because we could classify and separate the pattern fabrics reliably and efficiently.

4.3. Study of the digital characteristics of images by a *post hoc* test

From the previous part, we presumed that the differences between some of the means were statistically significant. For this, we analyzed the data using the *post hoc* test method. This type of test was only used after finding a statistically significant result and needing to determine the primary source of this difference. *Post hoc* tests attempt to control the experiment's error rate (usually alpha = 0.05). In Table 15, we analyzed the data using the t-test method (two-sample assuming equal variances). We analyzed the weave groups of the fabrics in pairs.

We divided the original alpha level (0.05) by the number of tests (3). Then, the result was a Bonferroni-corrected value (0.0167), which is the current threshold. In the previous table, we analyzed the row corresponding to ($P\,(T \leq t)$ two-tailed). As a result, we found the following results:

- In the first case (t-Test 1), we found a significant difference between the plain and the twill. This result is observed because $1.63 \times 10^{-26} < 0.0167$.
- In the second case (t-Test 2), we do not find a significant difference between the plain and the satin. This result is observed because 0.39 > 0.0167.
- In the third case (t-Test 3), we found a significant difference between the twill and the satin. This result is observed because $5.24 \times 10^{-21} < 0.0167$.

Table 13. Detailed report of the statistical analysis based on the CDL criterion

Groups	Number of samples	Sum	Average	Variance
Plain	25	376	15.04	49.04
Twill	32	1545	48.28	33.43
Satin	15	194	12.93	71.35

Table 14. ANOVA based on the CDL criterion

Source of variations	Sum of squares	Degree of freedom	Mean of squares	*F*	Probability	Critical value for *F*
Between groups	20630.51	2	10315.25	221.56	9.259×10^{-31}	3.12
Within groups	3212.36	69	46.55			
Total	23842.87	71				

Table 15. *t*-Test: two-sample assuming equal variances based on the CDL criterion

	***t*-Test 1**		***t*-Test 2**		***t*-Test 3**	
	Plain	**Twill**	**Plain**	**Satin**	**Twill**	**Satin**
Mean	15.04	48.28	15.04	12.93	48.28	12.93
Variance	49.04	33.43	49.04	71.35	33.43	71.35
Observations	25	32	25	15	32	15
Pooled variance	40.24		57.26		45.23	
Hypothesized mean difference	0		0		0	
Degrees of freedom	55		38		45	
t Stat	−19.63		0.85		16.79	
$P(T \leq t)$ one-tailed	8.16×10^{-27}		0.19		2.62×10^{-21}	
t-Critical one-tailed	1.67		1.68		1.67	
$P(T \leq t)$ two-tailed	**1.63×10^{-26}**		**0.39**		**5.24×10^{-21}**	
t-Critical two-tailed	2.00		2.02		2.01	

Table 16. Statistical presentation of data based on all criteria

		Plain	**Twill**	**Satin**
CDL	Mean	15.04	48.28	12.93
	Standard deviation	7.00	5.78	8.44
SSV	Mean	53.76	16.18	11.73
	Standard deviation	11.24	5.53	5.88
SSH	Mean	53.32	22.03	31.46
	Standard deviation	9.96	5.82	12.98
IBL	Mean	17.64	16.53	45.80
	Standard deviation	5.39	4.93	9.45

This study has statistically and scientifically shown the impact and significant difference between the different fabric patterns studied based on the “CDL” criterion. To have a more general idea of the effect of various measures on identifying fabric patterns, we proposed in Table 16 a statistical study based on all the parameters. In this table, we calculated the data’s mean and standard deviation related to all the parameters characterizing the image. We studied the classes of fabrics patterns (plain, twill, and satin) in this part.

After that, we graphically present these data to highlight a comparison between the means and the standard deviations.

Figure 8 shows that the characteristics chosen to describe the images of the weaves of the fabrics could classify and distinguish the groups efficiently. Indeed, the parameter “CDL” gave significantly higher values for the twill weaves with some approximate equality for the other two types of weaves. We noticed an apparent difference in the parameter “IBL” for the satin weaves compared to the two other weaves. Finally, to differentiate the plain weaves, we found the two criteria “SSV” and “SSH”. We observed a clear difference between the plain weave and the other two types, with a slight difference between the twill and the satin for the parameter.

4.4. Importance of integrating image processing and AHP

Our approach is better than the fabric’s previous pattern methods in terms of recognition. While conventional methods have been limited to the extraction of features and classification using simple algorithms, our approach of integrating image processing with the AHP has the following benefits.

First, this combination made the decision better because it offered a step-by-step procedure that enabled one to state the characteristics of the fabric in question based on its importance. It thus beats systems that are solely based on numerical values. Second, our approach is more accurate because it could consider the subjective features of fabric patterns, which are often not considered in similar methods.

Our method was also found to be versatile. AHP could be applied in any culture since it is possible to include expert judgments and thus tailor the evaluation to the application or the user’s opinion. In addition, AHP enabled a comprehensive analysis of the characteristics of fabric patterns from qualitative and quantitative points of view, something that other methods have limited to numerical data.

4.5. Practical implications and limitations

4.5.1. Practical implications

The methods presented in this study for automatically recognizing woven fabric patterns have practical implications for everyday life, especially in the textile and clothing industries. The time and labor required for manual inspections can be significantly decreased, leading to increased efficiency on the production lines. This automation also enhances quality control, as common defects or inconsistencies can be rapidly

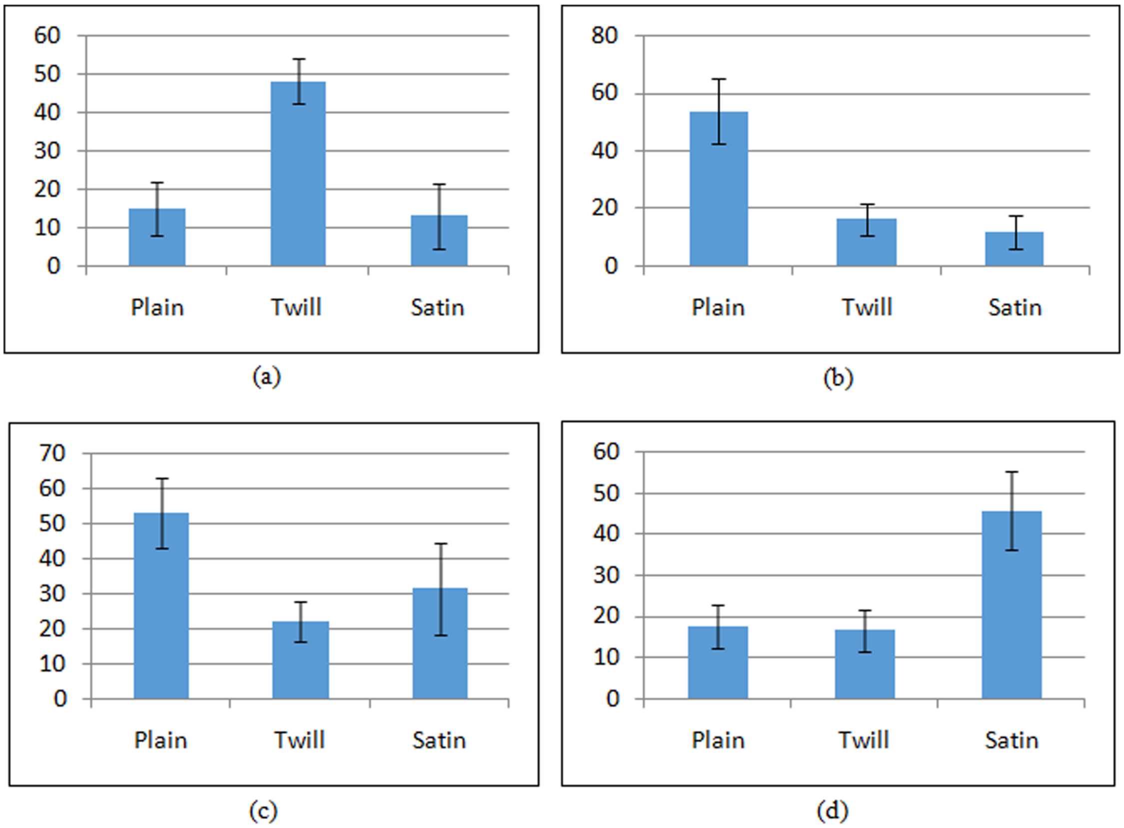

Figure 8. Comparative study for statistical data between classes of fabric weaves based on all criteria. (a) Rate of CDL. (b) Rate of SSV. (c) Rate of SSH. (d) Rate of IBL.

detected, which assures that higher quality standards are maintained. Designers can also use the system to quickly analyze and classify fabric patterns, which will, in turn, stimulate creativity for the creation of new designs.

4.5.2. Limitations

Despite the advantages of the proposed methods, they have some limitations. For example, the efficiency of image analysis depends very much on the quality of the images captured; poor lighting or low camera resolution can lead to failures in pattern recognition. Moreover, the system may not work well with very detailed or completely unusual fabric patterns. Some of the parameters used in the analysis, for example, CDL and other parameters, may be sensitive to minor variations in texture, leading to inconsistent results across different fabric types.

5. Conclusions

In this work, we used image processing techniques to eliminate the noise introduced in the image by the filtering method and homogenize the distribution of pixel intensity to obtain more significant results. The present article used image processing to identify the weaving fabric's density. The detection method consisted of applying filtering, histogram equalization, and thresholding to obtain a binary image. After that, we applied a calculation program based on recognizing shapes and the extraction of digital information from the images of the weaves of fabrics. Then, we used the AHP to classify the weaves by building a system whose inputs are the previously determined image characteristics. The output is the determination and identification of the nature of the pattern fabric (plain, twill, and satin). Finally, we used statistical tools (ANOVA method) to finalize our work to check the separation between the pattern classes. By evaluating our system, we found a strong correlation between the results obtained by our system and the actual results determined by experimentation.

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Conflict of interest: The authors declare there is no conflict of interest.

Ethical approval: The conducted research is not related to either human or animal use.

Data availability statement: The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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