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# Fabric Weave Pattern Detection Based on Fuzzy Clustering and Texture Orientation Features in Wavelet Domain

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**Abstract**

Automatic fabric defect detection plays an important role in textile industry. In this paper, a novel weave pattern detection method based on multiscale wavelet features and fuzzy clustering approach is proposed to tackle the problem in automatic weave pattern detection of woven fabric. Fuzzy C-means (FCM) clusters the multiscale features of the crossed areas of the fabric into two clusters. The state of the crossed area is determined by texture orientation features. The weave pattern is detected using the crossed area states. Since the proposed detection scheme requires few features, the amount of computational load involved is not significant. Moreover, an error correction algorithm has been added to correct the detection errors in some crossed areas. The performance of the proposed method is validated with plain and twill fabric images.

**Keywords:** Fabric crossed area; Fuzzy C-means clustering; Wavelet transform; Weave pattern; Woven fabric

## Introduction

Textile fabrics constitute a large proportion of the total cost of production in garment manufacturing. Quality control of fabrics before garment manufacturing is essential to ensure the quality of finished products and to increase the efficiency of the manufacturing process. Inspection of weave pattern in textile industry plays an important role in the quality control. Evaluation of fabric weave pattern in textile industry depends on manual operation with the help of microscope [1-8]. This process is very tedious and time consuming. Moreover, subjective nature of this kind of inspection leads to variation in quality assessment. An optimal solution for this would be to automatically inspect from the fabric as it is being produced and to alert the maintenance personnel when the machine needs attention to change process to improve product quality. Automated visual inspection of fabric texture increases the efficiency of production system and improves quality of product [9-13].

Weave pattern is one of the structural characteristic of the woven fabrics. Woven fabrics are formed by interlacing two sets of mutually perpendicular yarns in vertical and horizontal direction namely "warp" and "weft". The way in which the warp and the weft threads interlace with each other is called the weave. Weave pattern refers to the basic unit of weave that is periodically repeated throughout the entire fabric area. The automatic recognition of weave patterns has been reported by many researchers. Generally, two main approaches are used, first is to extract global texture features using statistical, spectral or model based approach and use a learning classifier to recognize weave pattern [8-23]. The second approach is to detect the weave pattern crossed area states, i.e., whether weft float (weft is interlaced over warp) or warp float (warp is interlaced over weft) is present in the detected crossed area [9-14,24-27].

Kinoshita considered the optical components of the diffraction image for the structural recognition of woven fabrics [1]. Escofet et al. used the Fourier image analysis technique to locate the weft and warp crossed areas [3]. Other statistical methods like edge using lookup table, Auto-correlation, co-occurrence matrix and neural networks are computationally very demanding if the template size used is large [4-8]. All this approaches are very sensitive to the selection of the set of training data used for the learning algorithm. Variations in the lighting condition and the image scale may lead to a failure of the classifier. Moreover, once a weave pattern is erroneously recognized by the classifier, it cannot be corrected.

Lachkar et al. utilized 2D Fast Fourier Transform and T. J. Kang et al. performed 2D-autocorrelation to find the widths of weft and warp. As the widths of the yarns are not uniform, errors may occur when locating the crossed area of unevenly distributed yarns [11].

Kuo C et al. developed an unsupervised automatic recognition method using fuzzy C- means clustering [12]. They used FCM to classify the detected crossed areas into two clusters. However, their method failed to decide the crossed area states, whether the weft or the warp floats in a specific crossed area. Xin Wang et al. proposed a weave pattern recognition method using Gray Level Co-Occurrence (GLCM) features and FCM. Their method decides the crossed area states, but it is computationally complex [13].

The recent weave pattern detection algorithms are not sufficient to give the accurate and precise result. They are time-consuming and fail to correct the detection errors in some crossed areas. We propose a novel method for solving the issues to recognize the weave pattern of woven fabric. Integral projection is used to segment the crossed area of unevenly distributed yarns. Multiscale Texture features of the segmented crossed areas are extracted using wavelet transform. FCM classifies the multiscale texture features into two different clusters of crossed areas. The texture orientation features of the clusters determine the exact state of the crossed area which determines the weave pattern. An error correction method has been added to correct the erroneously detected crossed area states.

This paper is organized as follows: In section 2, we propose a new method for the automatic recognition of the weave pattern in woven

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fabric. The experimental results obtained are briefly explained in section 3. The paper is concluded in Section 4.

## Methodology

Weave patterns are designed to achieve aesthetic or functional features. Weave pattern perception is one of the most important fundamental factors in textile design process. Traditional detection of fabric weave pattern requires extensive manual operation and also very time- consuming for designers to manually check the weave patterns one by one. Automatic detection of weave pattern in woven fabrics avoids such problem. The weave pattern detection comprises of an automatic segmentation of weave pattern of the fabric image. The steps involved in the weave pattern recognition are shown in Figure 1.

The input fabric image is first processed to remove artifacts due to non-homogeneous lighting and camera lens dirt. A spatial domain median filter, which is small and fast, is used to reduce the noise caused by original image acquisition. The histogram equalization is performed to enhance the quality and the visual perception. The yarn crossed area is detected by integral projection approach from interlacing areas of the horizontal and vertical projection curve of the fabric image. FCM clusters the detected crossed areas into two clusters based on wavelet features. The clusters represent the weft and warp floats in the fabric image. A decision algorithm based on texture orientation features determine the exact float of the clusters and represented in a pattern matrix of ones and zeros.

### Fabric crossed area detection

Image of woven fabric is a structured texture image. Woven fabrics are formed by two sets of mutually perpendicular interlaced yarns termed as "warp" (vertical yarns) and "weft" (horizontal yarns) [11,12]. The way in which the warp and the weft threads interlace with each other is called the weave or crossed area of the yarn. Interstices found between yarns display darkness that is, the pixels around them have relative lower grey levels. Weave pattern refers to the basic unit of weave that is periodically repeated throughout the entire fabric area [20]. The intersecting area between weft yarn and warp yarn is detected using integral projection approach [11,13]. The existence of the regularity of the local minima along a particular orientation at a particular scale can be measured using the projection profile along that orientation in an image window. Using this approach, horizontal and vertical projection curves of the fabric image is obtained. For an image $(x, y)$ of size $M$x$N$, the horizontal projection curve PHR ( I ) ( y) and vertical projection curve PVR (I)(x) are given by:

$$P_{HR(I)}(y)=\sum_{x=1}^{N} I(x,y) \text{ and } P_{VR(I)}(x)=\sum_{y=1}^{M} I(x,y)$$

The undesired local minima present in the projection curves are removed by smoothing the projection curves using the 3 x 3 spatial masks. Let $f_1$(y) and $f_2$(x) be the smoothed horizontal and vertical projection curves. For the smoothed horizontal projection curve $f_1$(y), local minima point occurs at $y^*$, if $f_1(y^*) \leq f_1(y)$ when $|y-y^*| < a$, where, a is a scalar constant. Similarly, for the smoothed vertical projection curve $f_2$(x), local minima point occurs at $x^*$, if $f_2(x^*) \leq f_2(x)$ when $|x-x^*| < b$, where b is a scalar constant. The lines drawn through the local minima of the horizontal projection curve form the warp separation lines and through the local minima of the vertical projection curve form the weft separation lines. Intersection of the warp separation lines and the weft separation lines give the crossed-areas of the yarn. Figure 2 shows the detected crossed areas of the fabric image.

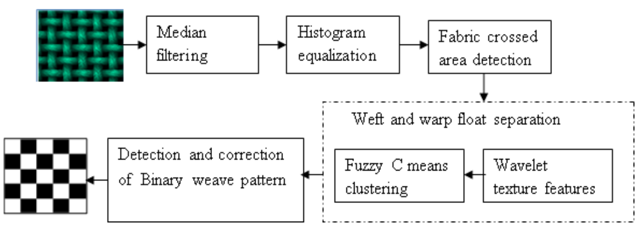


**Figure 1:** Automatic weave pattern recognition.

### Weft and warp float separation

The crossed area of woven fabric consists of interlacing of weft and warp yarns. There are two possible states in woven fabric, in which the warp is floating over the weft or vice versa. Weft float is formed when weft is interlaced over warp and warp float is formed when warp is interlaced over weft. Based on the wavelet texture features of the crossed areas, these two floats are separated [15].

**Wavelet transform:** The wavelet transform has been widely used in data compression, signal and image analysis. The wavelet transform maps a function onto a scale-space plane with varying scales and orientation. Wavelet transform is the representation of the function by mother wavelet. The wavelets are obtained from a single prototype mother wavelet function $\psi$ defined as:

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

Where a, b are the scale and translation parameters. Discrete wavelet transform captures both the spatial and frequency information of the image. Wavelet transform decomposes the fabric texture image into coarse approximation and detail information correspond to different directions and scales using the low pass filter $g(n)$ and the high pass filter $g(n)$. The approximation coefficient $W_\phi(j_{0,}\ m, n)$ of an image I (x, y) at scale $j_0$ is given by

$$W_\phi(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} I(x,y)\phi_{j,m,n}(x,y) \qquad (3)$$

The detail coefficients $W^i_\psi$ *(j, m, n)* along horizontal (H), vertical (V) and diagonal (D) directions are:

$$W^i_\psi(j.m.n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} I(x,y)\psi^i{}_{j,m,n}(x,y) \qquad (4)$$

Where I = [H,V,D] and j= 1. (*j m n*) (x,y) and $\psi^i_{j,m,m}$(x,y) are the set of orthonormal basis functions generated by dilation and translation of scaling function φ and a mother wavelet ψ.

The image is decomposed into four directions corresponding to 0° (horizontal-A), 45° (diagonal-Dd), 900(vertical-Dv) and 135° (diagonal-Dh) using the low pass and high pass filters. In the first level of decomposition, the image is separated into four sub-bands as illustrated in Figure 3. They are called approximation (Low Low or LL), horizontal (Low-High or LH), vertical (High-Low or HL) and detail coefficients (High-High or HH). Most of the energy is contained in the top left (L-L) subband image and the least energy is in the lower right (H-H) sub image. Hence, the approximation coefficients obtained in the first level can be used for the next decomposition level. By applying the decomposition to the low-frequency component again, the four components of the image of lower resolution are obtained. As a result of two level decompositions, we get two approximation coefficients and six detail coefficients.

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Daubechies (db) wavelet is the mostly used mother wavelet for texture feature extraction due to its orthogonal property; this has good localization and is used for texture classification. Since the db wavelets have highest number of vanishing moments for a given support, the scaling function can represent more complex patterns accurately. Also it does not imply any smoothening on the texture. The Daubechies wavelet of order 4 is used in this work. Wavelet coefficient first-order statistics features like mean, variance, skewness, kurtosis, entropy and energy are calculated from the wavelet coefficients.

**Fuzzy c-means clustering:** The two possible states in woven fabrics are, the warp is interlaced over the weft and weft is interlaced over the warp as in Figure 4. An unsupervised clustering method is used to classify the different states of the fabric based on the features. Fuzzy c-means is an unsupervised clustering algorithm that has been applied in problems involving clustering and classifier design [16]. The FCM is based on the minimization of the following objective function:

$$j_{fcm} = \sum_{i=0}^{m}\sum_{k=1}^{c} u_{ik}^{q}\left\|y_i - c_k\right\|^2 \quad (5)$$

Where $u^{q}_{ik}$ is the membership function of i vector with respect to cluster k with values between 0 and 1; $c_k$ is the cluster center; $q$ is a weighting exponent on each fuzzy membership and determines the amount of fuzziness; $m$ is the number of vectors and $c$ is the number of clusters. $\| y_i - c_k \|$ vis the distance between the sample $y_{i\,a}$nd the centers of classes $c_k$. The calculation of the membership partition matrix $u_{ki}$ and the cluster center $v_i$ are performed as follows:

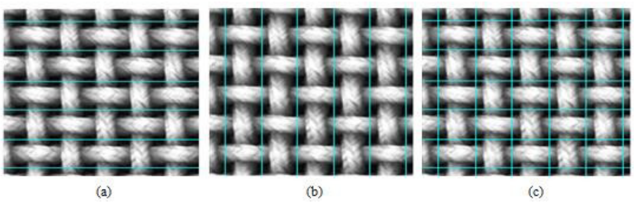

**Figure 2:** Fabric crossed area detection (a) Warp separation line (b) Weft separation lines (c) Detected crossed-areas.

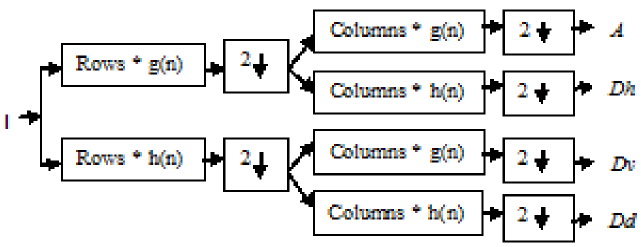


**Figure 3:** 2D DWT decomposition.

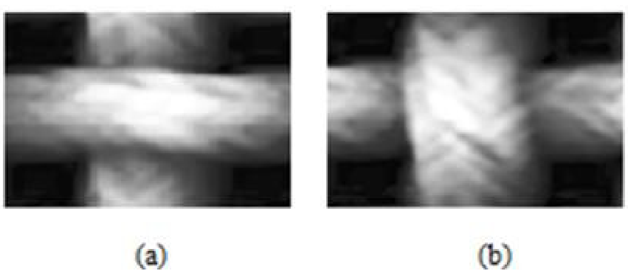

**Figure 4:** Segmented crossed-areas (a) weft float (b) warp float.

$$u_{ki} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\left\|y_i - c_k\right\|}{\left\|y_i - c_j\right\|}\right)^{2/q-1}} \quad (6)$$

$$v_i = \frac{\sum_{i-1}^{m} u_{ik}^{q} y_i}{\sum_{i-1}^{m} u_{ik}^{q}} \quad (7)$$

The constrained optimization problem in this algorithm is solved using Lagrange multipliers. The closed-form formula for updates of membership function and cluster center is derived by taking the partial derivatives of the objective function with respect to both and setting them to zero. The optimization problem is solved by iteratively updating degrees of membership with fixed centers and updating centers with fixed degrees of membership. The fabric image has $m$ detected crossed areas and each crossed area is represented by feature vector with 54 elements. The two clusters obtained using FCM for plain and twill weave with $c$=2, $m$=2 is illustrated in Figure 5.

**Weave pattern detection and error correction:** The detected crossed area comes under any one of the two possible states namely weft float and warp float. Weft float is formed when weft is interlaced over warp and warp float is formed when warp is interlaced over weft. Since the weft and warp float forms the structure of the woven fabric, the orientations of the texture in detected segments are different depending on the type of the float. The texture orientation features are used to determine the exact states of the float. The texture orientation feature (TO) is the grey-level difference between the pixels according to their distance d [11]. Let I (x, y) be the segmented crossed area with size $M$x$N$, then TO along row and column is given as:

$$TO_{row} = \frac{1}{M(N-D)}\sum_{y=1}^{M}\sum_{x=1}^{N-d}[I(x,y) - I(x+d,y)]$$

$$TO_{row} = \frac{1}{N(M-D)}\sum_{X=1}^{N}\sum_{y=1}^{M-d}[I(x,y) - I(x+y,d)]$$

Let $TO_{row}C1$, $TO_{col}C1$, $TO_{row}C2$, $TO_{col}C2$ be the mean texture orientation features of the two clusters C1 and C2. The decision of the clusters, whether they are weft or warp float is decided by the following conditions:

*Float={C1 is weft & C2 is warp, if* $TO_{row}C1 > TO_{row}C2$ *&* $TO_{col}C1 < TO_{col}C2$
*C1 is warp & C2 is weft, otherwise*

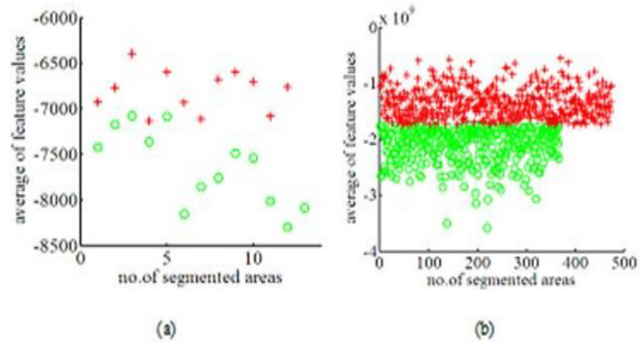


**Figure 5:** Clustering of two possible states in the crossed areas (a) Plain weave (b) Twill weave.

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Weft float and warp float are denoted by 0's and 1's. Let P be the matrix which represents the segmented cross areas of the fabric image with weft and warp float (0's and 1's). P represents the detected weave pattern. Let the weave pattern B is the basic unit of weave that is periodically repeated throughout the entire fabric. Thus, P can be formed by tiling the randomly selected basic unit of weave pattern periodically. The size of basic weave pattern B is found from the 2D auto correlation of P. Let Q be the matrix formed by tiling B. The number of different elements in Q and P is used to find the error in the detected pattern. B with minimum error is taken as basic weave pattern and forms the error free fabric structure.

## Results and Discussion

Woven fabric images of plain and twill type with 256 gray levels are used to evaluate the proposed method. These images have different weave types, fiber appearances, and yarn counts. The samples of images are shown in Figure 6. The images p1 to p4 represent the plain weave and t1 to t4 represents the twill weave. Gray scale images were obtained from the RGB form, thereby discarding the color information. The images are pre-processed using median filtering and histogram equalization to enhance the quality and the visual perception. Matlab is used to develop the algorithm. The output image contained a noise free uniform distribution of intensities to increase the dynamic range of the histogram of an image. Figure 7 shows the enhanced version of image p1 and t1.

Fabric crossed areas are detected using horizontal and vertical projection curves. The undesired local minima in the projection curves are removed using moving average filter of size 11 × 11. Figure 8 shows the projection curve before and after smoothing. Using the smoothed projection curves, interlacing lines are drawn through the local minima points. Warp separation lines are drawn through the local minima of horizontal projection curve and weft separation lines are drawn through the local minima of vertical projection curve. Interlacing of these two lines form the cross area as in Figure 2.

The detected weave pattern using texture orientation features is shown in Figure 9. Such fabric patterns of images obtained at this stage may or may not contain error. The black area represents the warp float and white area represents the weft float. The error corrected fabric pattern obtained by tiling the basic weave pattern of images p1, p2, p3, p4, t1, t2, t3 and t4 are shown in Figure 10.

### Detection error rate

The performance of the proposed method is evaluated on real and computer simulated fabric images. The recognition rate of the weave pattern improves after error correction. However the recognition rate for the computer-simulated images is 100% before the error correction module. The error rate for real fabric samples are shown in Table 1. The error rate is independent of the fabric type i.e., plain or twill. The average error rate is less than 2%. The error may be caused by a local defect of the fabric surface, low quality of the fabric image, or by bad segmentation. Since more than 95% crossed area states are correctly detected, there cognition rate is increased to 100% after error correction. From the results, we can conclude that with the proposed method all type of weave structures in different samples having different weave pattern are accurately detected.

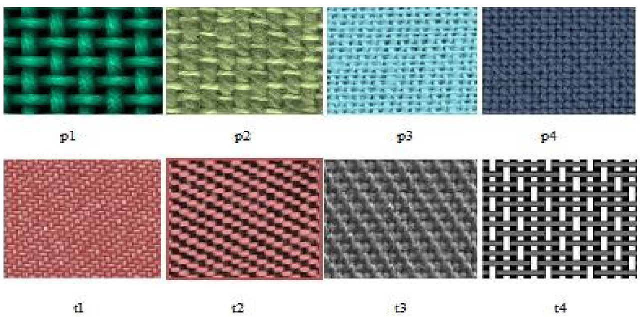


**Figure 6:** Samples of input image.

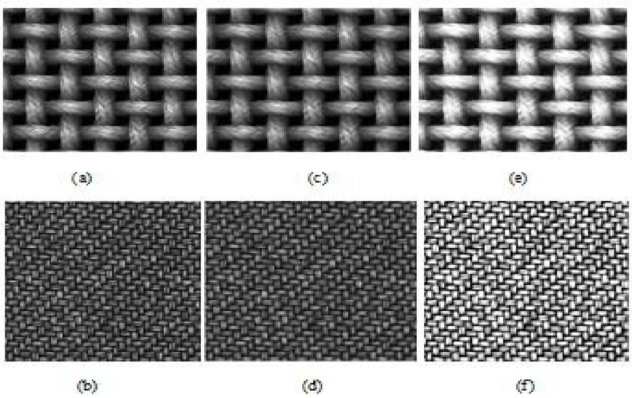


**Figure 7:** Enhanced images (a)-(b) Gray scale fabric image p1 and t1 (c)-(d) p1 and t1 after median filtering (e)-(f) p1 and t1 after enhancement.

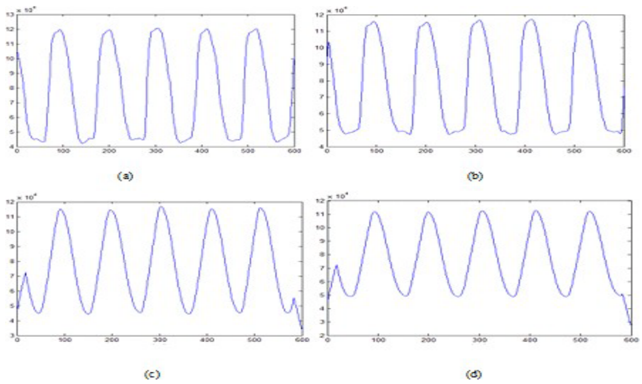


**Figure 8:** Projection curves and their smoothed versions (a) horizontal projection curve (b) vertical projection curve (c) Smoothed horizontal projection curve (d) Smoothed Vertical projection curve.

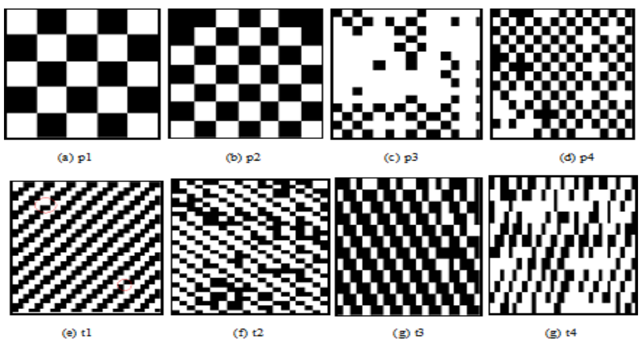


**Figure 9:** Detected weave pattern.

| Sample image | p1 | p2 | p3 | p4 | t1 | t2 | t3 | t4 | Average Error rate |
|---|---|---|---|---|---|---|---|---|---|
| **Error rate** | 0 | 0.02 | 0.02 | 0.028 | 0.026 | 0.029 | 0.029 | 0 | 0.019 |

**Table 1:** Error rate for real fabric images.

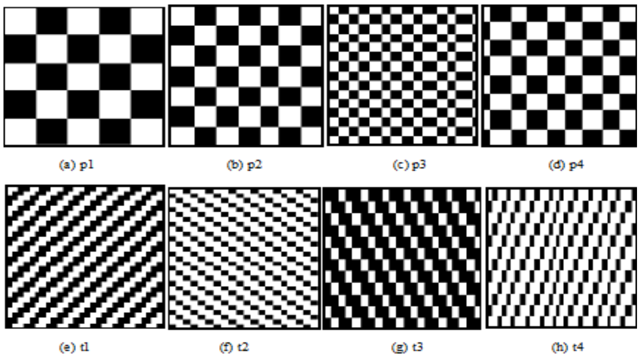


**Figure 10:** Error corrected fabric pattern.

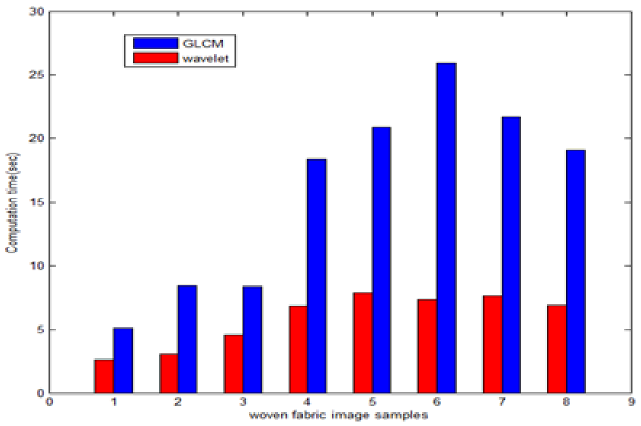


**Figure 11:** Comparison of computation time.

| Sample image | Error Rate | |
|---|---|---|
| | **GLCM** | **Proposed** |
| **p1** | 0.015 | 0 |
| **p2** | 0.02 | 0.02 |
| **p3** | 0.03 | 0.02 |
| **p4** | 0.028 | 0.028 |
| **t1** | 0.028 | 0.026 |
| **t2** | 0.035 | 0.029 |
| **t3** | 0.03 | 0.029 |
| **t4** | 0.02 | 0 |

**Table 2:** Comparison of detection error rate for GLCM and wavelet features.

The detected crossed-area segment in the proposed method is decomposed into nine high frequency sub bands using the Daubechies wavelet. For each crossed-area segments we have 54 features which are quite small when compared to 192 GLCM features after dimensionality reduction using principle component analysis [13]. As the number of crossed-area segment increases, GLCM requires large storage space and thus the computational complexity of this method increases. Thus, by using wavelet feature extraction method the computational complexity is reduced to large extent. Figure 11 shows the comparison of computation time between the GLCM feature extraction method and wavelet feature extraction method for plain and twill weave. The computation complexity of the proposed method is nearly 25% less than GLCM features for plain weave and 50% for twill weave. From the figure, we can conclude that the computational complexity of the wavelet feature extraction method is less compared to GLCM feature extraction method.

Table 2 shows the effectiveness of the wavelet feature extraction method in error detection compared with GLCM features. Comparison results are given for 4 plain and 4 twill weaves. Using GLCM method, the detection error rate for twill weave is more compared to the plain weave. Wavelet transform provides a precise and unifying frame work for the analysis and characterization of the 2D signal at different scales, with reduced inter-scale correlation among the resulting texture components. The results show that the performance of the proposed method is found to be better when compared to the GLCM method.

## Conclusion

In this paper we proposed a method for automatic recognition of basic weave pattern of woven fabric. The two crossed area states in the weave pattern are detected from the multiscale wavelet features using Fuzzy C means clustering algorithm. The texture orientation features of the crossed areas determine the exact state of the crossed area. A binary pattern matrix is obtained from the detected crossed area states. Finally, an error correction method has been employed to correct the errors in some crossed areas and, the corrected pattern is obtained. The method is validated using computer-simulated woven fabric samples and real woven fabric images. Wavelet analysis reduces the number of features required for the detection of weave pattern, which in turn reduces the required memory space and computational complexity of the system. More than 95% of the weave pattern is correctly detected and the recognition rate increased to 100% after error correction.

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