

Research Article

Fabric Defect Detection Using Modified Local Binary Patterns

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Local binary patterns (LBPs) are one of the features which have been used for texture classification. In this paper, a method based on using these features is proposed for fabric defect detection. In the training stage, at first step, LBP operator is applied to an image of defect free fabric, pixel by pixel, and the reference feature vector is computed. Then this image is divided into windows and LBP operator is applied to each of these windows. Based on comparison with the reference feature vector, a suitable threshold for defect free windows is found. In the detection stage, a test image is divided into windows and using the threshold, defective windows can be detected. The proposed method is multiresolution and gray scale invariant and can be used for defect detection in patterned and unpatterned fabrics. Because of its simplicity, online implementation is possible as well.

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1. INTRODUCTION

Defect detection is an important problem in fabric quality control process. Cost reduction in production and inspection process is also an important objective for textile manufacturers. At present the quality inspection process is manually performed by experts. Typical fabrics are 1–3 m wide and are driven with speeds ranging from 20 to 200 m/min. Experts cannot detect more than 60% of the overall defects if the fabric moves faster than 30 m/min or wider than 2 m [1]. Like other inspection processes, it has depended on workers' experience until now. The development of a flexible, efficient, reliable, and integrated real-time vision system for industrial application is an essential issue in quality control process for textile manufacturers. In particular, if there is a defect, it reduces the price of the fabric by 45%–65%. To increase the overall quality, the homogeneity of fabric, and reliability, an automated visual inspection system is needed for better productivity. Therefore, automation of visual inspection tasks can increase the efficiency of production lines and improve quality of the products as well. The previous works in the field of automatic defect detection are mainly done on paper [2], steel roll [3], wood [4, 5], carpet [6], and textile [7–11]. Most of the automatic fabric inspection systems are offline and have detection speed up to 100 m/min. An important point regarding these systems is that each of them can only

detect specific types of the defects. Therefore, detection speed and the range of the detectable defects are two main issues in the field of automatic fabric inspection.

Many attempts have been made in the past three decades to solve these problems. These attempts have been based on three different approaches: statistical, spectral, and model based. In statistical approach, gray-level texture features extracted from cooccurrence matrix [12], mean and standard deviations of subblocks [13], autocorrelation of subimages [14], and Karhunen-Loeve (KL) transform [15] have been used for the detection of fabric defects. Bodnarova et al. [16] made use of normalized cross-correlation functions for detecting defects in fabrics. There exist many model-based techniques for fabric defect detection. For example, Cohen et al. [17] used a Markov random field (MRF) model for defect inspection of fabrics. Chen and Jain [18] used a structural approach to detect defects in textured images. Atalay [19] has implemented an MRF-based method on TMS320C40 parallel processing system for real-time defect inspection of fabrics. Methods that use low-order MRF are not capable of detecting all kinds of the defects in fabric texture. In order to detect all kinds of the defects, the order of the model should be increased. This yields an increase in computational complexity of the algorithm. There also exist many spectral approaches for fabric defect detection. For example, Kumar and Pang [20] proposed a method for defect detection using

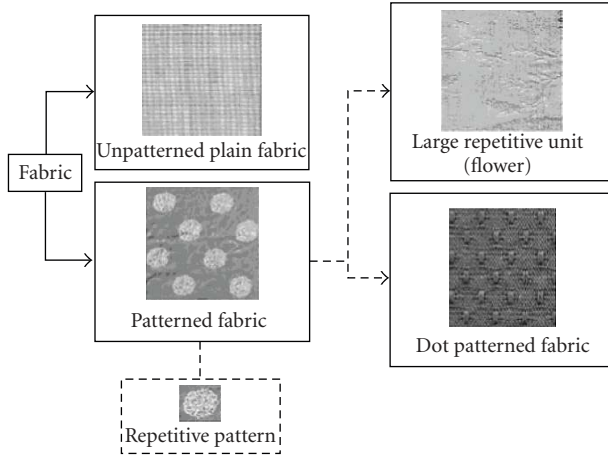


FIGURE 1: Classification of fabrics [23].

Gabor filters which needs a large amount of computations. They also developed a method for defect detection using only imaginary part of Gabor filters. Chan and Pang [21] offered a method for defect detection in textile fabrics using Fourier analysis. Since Fourier bases are of infinite length, the contribution from each of the spectral components is difficult to quantify. Therefore, Fourier analysis is not suitable for detecting local defects. Kumar and Pang [22] developed a method for defect detection in textile fabrics using optimized filters.

It should be noted that most of the researches about fabric defect detection are made on unpatterned fabrics and only a few works for defect detection in patterned fabrics have been reported. For example, Ngan et al. [23] used a wavelet-based method for defect detection in patterned fabrics. A patterned fabric is defined with repetitive patterned units in its design. Under the class of patterned fabric, there are many categories. Patterned fabrics that are used in this research are Jacquard patterned fabrics. In these types of fabrics a flower or a graphical logo may appear on the fabric. The repetitive unit can range from the simplest character box, dots, to the most complicated multiple flower, animals, or other designed patterns. Besides there are a lot of subcategories under patterned fabric. Figure 1 illustrates a classification of fabrics [23].

The researches in this area can be divided into two different categories. In the first category, all attempts are conducted to increase the range of the defects to be detected, while they need a large amount of computations. References [20–22] belong to this category. In the second one, increasing detection speed is the aim, while a restricted range of defects can be detected. References [12–19] belong to the second category.

In this paper, a simple and straightforward method for detecting irregularities in fabric texture is proposed, which can detect a wide range of the defects. In this method, local binary patterns (LBPs) are used. It should be noted that LBP is used for texture classification [24] but in this paper for the first time it is used for detecting textural defects in fabric. LBP is theoretically very simple, yet efficient approach for texture

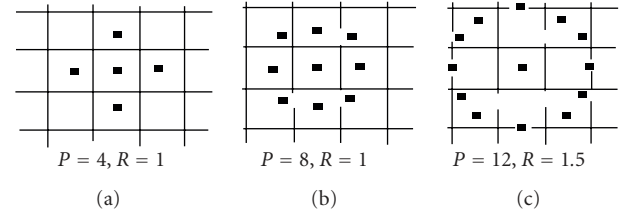


FIGURE 2: Circularly symmetric neighborhoods for different P and R [24].

classification. This method is based on recognizing that certain LBP features are fundamental properties of local image texture and their occurrence histograms are proven to be a very powerful texture feature [24]. LBP is a highly discriminative texture operator. It records the occurrence of various patterns in neighborhood of each pixel in P -dimensional histograms. Therefore, this method is used for detecting textural defects in fabric. The proposed method is simple, multiresolutional, and invariant to gray scale. Experimental results show that a wide range of the defects can be detected through this method. This method is applicable for defect detection in both unpatterned and patterned fabrics which have a repeated and periodic texture.

This paper is organized as follows: in Section 2, local binary patterns are described in its basic and modified versions. In Section 3, the proposed method for defect detection is presented. Section 4 is devoted to implementation and experimental results and the conclusion is provided in Section 5.

2. USING LBP IN TEXTURE CLASSIFICATION

One of the methods used in texture classification is LBPs [24]. In this method, a neighborhood of the image is considered and the gray value of the pixel in the center is compared with the gray values of the other pixels in the neighborhood. Usually the neighborhood is in circular form and the gray values of the neighbors which do not fall exactly in the center of pixels are estimated by interpolation. Figure 2 illustrates circularly symmetric neighbor sets for various radii, R , and different numbers of neighbors, P .

In basic form of this method, LBP operator in one neighborhood of the image is defined as follows [24]:

$$\text{LBP}_{P,R} = \sum_{i=0}^{P-1} s(g_i - g_c) 2^i, \quad s(x) = \begin{cases} 1, & x \geq 0, \\ 0, & x < 0. \end{cases} \quad (1)$$

In (1), the gray value of the central pixel is g_c and the gray value of the i th neighbor is g_i . According to this definition, it is seen that the output of the operator is a P bit binary number with 2^P distinct values. On the other hand, the value of the output is quite dependent on the labeling of the neighbors. When the image is rotated, since the neighborhood is considered in circular form, neighbors will correspondingly move along the perimeter of the circle. In order to make the algorithm invariant to rotation and assign a unique value to

each neighborhood, the output of LBP operator is rotated and the minimum value is selected:

$$\text{LBP}_{P,R}^{ri} = \min \{ \text{ROR}(\text{LBP}_{P,R}, i) \mid i = 0, 1, \dots, P-1 \}. \quad (2)$$

In (2), a P -bit number is rotated i times and the minimum value between resulting numbers for i between 0 to $P-1$ is selected. In (2), ROR is the abbreviation of rotate right.

In modified version of LBP [24], at first a uniformity measure, U , is defined as the number of spatial transitions between 1s and 0s in the pattern. Then patterns that have uniformity measure less than U_T are defined as uniform patterns. The modified LBP is defined as follows:

$$\text{LBP}_{P,R}^{riuT} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & \text{if } U \leq U_T, \\ P+1 & \text{otherwise.} \end{cases} \quad (3)$$

Equation (3) shows that modified LBP assigns labels from 0 to P to uniform neighborhoods and label $P+1$ to nonuniform ones. After applying this operator to the image, the probability of encountering a specific label can be approximated by the ratio of the number of neighbors which have that label to the number of all neighbors. Therefore, at the end of this process $P+2$ probabilities will be computed. These probabilities can be used as powerful features for texture classification. For classification task, the log-likelihood ratio is used. The sample under test belongs to class K if the computed probabilities minimize the following ratio:

$$L(S, K) = \sum_{i=0}^{P+1} S_i \log \left(\frac{S_i}{M_{iK}} \right). \quad (4)$$

In (4), M_{iK} is the probability of encountering label i in the patterns of class K , and S_i is the probability of encountering label i found from the sample under test. According to (3), it is obvious that any monotonic change in gray values does not change the pattern and this method is invariant to gray scale changes.

3. THE PROPOSED ALGORITHM FOR TEXTILE DEFECT DETECTION

In this section, a new method for defect detection in fabrics, based on a modified version of LBP, is presented. In basic and modified versions of LBP, selecting neighborhood in circular form is to make the algorithm invariant to rotation. Since during inspection process, rotation of fabric rolls can be avoided, selecting circular neighborhood is not necessary. On the other hand, computing brightness using interpolation in circular neighborhood takes a lot of time. Therefore, in our proposed method, a square neighborhood is considered. In this case, the notation of LBPs is renamed from $\text{LBP}_{P,R}$ to LBP_{P,w_m} , where the size of the window for applying LBP operator is $w_m \times w_m$ pixel. Figure 3 illustrates square neighborhoods and how to apply the LBP operator. Using LBP operator, a label from 0 to $P+1$ is assigned to each neighborhood of the image. These labels reflect the relation between a pixel and its neighbors. We use the probability of

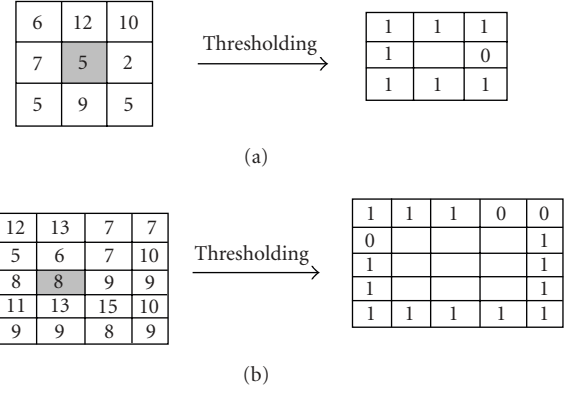


FIGURE 3: LBPs for two square neighborhoods: (a) $w_m = 3$, $P = 8$ and (b) $w_m = 5$, $P = 16$.

encountering these labels, as a key feature for our proposed defect detection method. Experimental results show that if the probability of encountering label $P+1$ which is assigned to nonuniform patterns is small (less than 1%) these features can classify the texture correctly, otherwise different patterns in the texture take the same label ($P+1$) and cannot be classified.

Our simulation results show that if in the definition of LBP operator the value of U_T is selected equal to $P/4$, only a negligible portion of the patterns in the texture takes label $P+1$.

In the subsequent sections, the proposed method for defect detection in unpatterned and patterned fabrics will be presented. Output of the proposed algorithm is a binary image which is called defect pattern. Black pixels in the defect pattern represent nondefective areas of the fabric and white pixels represent defective areas. The size of the defect pattern is the same as the size of the input image.

3.1. Defect detection in unpatterned fabrics

For detecting defects in unpatterned fabrics, in training stage, LBP operator is applied to the whole image of a defect free fabric and reference feature vector, M , is computed. Each element of this vector is the probability of encountering labels 0 to $P+1$ in the defect free image. If the number of points in LBP (number of pixels in the neighborhood) operator is P , the reference feature vector which is called M will be $P+2$ dimensional. After computing M , the image of the defect free fabric is divided into nonoverlapping windows of size $W_d \times W_d$ which are called detection windows. Then LBP operator is applied to each of these windows. The window for applying LBP operator is called LBP mask. Each element of the feature vector computed for a window is the probability of encountering a specific label in that window. In order to estimate these probabilities accurately, the number of operators applied to each detection window should be large enough (as a rule of thumb, at least 100 operators in each window). If the size of the detection window is $W_d \times W_d$ and the size of LBP mask is $w_m \times w_m$ ($W_d \gg w_m$), then the number of operators in each window will be $(W_d - w_m + 1)^2$.

Therefore, if the minimum number of operators applied in each window is 100, then $W_d \geq 9 + w_m$.

It should be noted that the features extracted by LBP operator can describe fabric texture correctly if the textures appeared in detection windows are similar to fabric texture. Therefore, the size of the detection window ($W_d \times W_d$) created on the image should be greater than the size of the repetitive unit of fabric texture. However, in unpatterned fabrics the only condition for window size is $W_d \geq 9 + w_m$. As the size of the detection window increases, the capability of the algorithm in detecting small defects and the resolution of the defect pattern decrease. By applying LBP operator to each of these windows, vector S_k which is $P + 2$ dimensional is computed. The log-likelihood ratio for each of these windows will be computed as follows:

$$L_k(S_k, M) = \sum_{i=0}^{P+1} S_{ik} \log\left(\frac{S_{ik}}{M_i}\right), \quad k = 1, 2, \dots, N. \quad (5)$$

In (5), N is the number of detection windows. Since the minimization of log-likelihood ratio shows the similarity to a specific class, the maximum value between these ratios will be used as a threshold for defect-free windows as follows:

$$T = \text{Max}(L_k), \quad k = 1, 2, \dots, N. \quad (6)$$

After computing reference feature vector M and the threshold T , in the detection stage, the test image is divided into the detection windows and log-likelihood ratio is computed for each of these windows. If log-likelihood ratio exceeds the threshold, the relevant window belongs to the defective areas of the fabric. In order to increase the detection capability of the algorithm, a large area of the detection window should be occupied by the defect. Therefore, in the detection stage, image is divided into overlapping windows. According to the simulation results, if the overlapping step of the detection windows is $W_d/2$, the proposed algorithm has appropriate detection power. Increasing overlapping step will decrease detection speed.

3.2. Defect detection in patterned fabrics

For detecting defects in patterned fabrics which have a periodic texture, in training stage, as it was mentioned in the previous sections, at first LBP operator is applied to the whole image of a defect free sample then the image is divided into the detection windows and LBP operator will be applied to each of these windows. Since the fabrics are patterned if the size of the window is less than the size of the repetitive unit in the fabric texture, then the texture in the detection windows will be different. So, the size of the detection window should be much greater than the repetitive unit of the fabric texture. Increasing the size of the detection window will increase computational complexity and decreases the resolution of the defect pattern. In order to solve this problem, the size of the detection window will be chosen a little greater than the size of the repetitive unit in the fabric texture and in order to take into account the interaction between all pixels with their neighbors, the image is divided into overlapping

windows. In this case, if the size of LBP mask is $w_m \times w_m$ pixel, overlapping step of $w_m - 1$ between detection windows is sufficient to take into consideration the interaction between all pixels in different detection windows (interaction between pixels in the last column and the last row of a window with pixels in the first column and the first row of the adjacent window). Using these types of windows, the threshold is computed as in (5) and (6). The remaining stages are as for unpatterned fabrics. It should be noted that this method is a multiresolution and the results of selecting different windows can be combined easily as follows:

$$L_K^N = \sum_{n=1}^N L_K(S_K^n, M^n), \quad (7)$$

where N is the number of windows (neighborhood) selected for applying LBP operator and K is the index of the testing window. The overall block diagram of the proposed algorithm is shown in Figure 4.

It should be mentioned that, in the training stage, if the number of defect free sample is N_{df} , then the reference feature vector can be estimated more accurately using

$$M = \frac{\sum_{i=1}^{N_{df}} M_i}{N_{df}}, \quad (8)$$

where M_i is the reference feature vector computed for sample i . After computing the reference feature vector, M , the threshold is computed using

$$T = \max_i(T_i), \quad (9)$$

where T_i is the threshold computed for sample i using (5) and (6) and computed M .

4. IMPLEMENTATION AND RESULTS

In this research, two types of unpatterned fabrics, twill and plain, are used. Six different types of the defects like double yarn, missing yarn, broken fabric, weft crack, float, and knots in these types of fabrics are considered. These defects are shown in Figure 5. All these fabrics have yarns of different thicknesses, and their warp and weft direction thicknesses are also different. Detection results for unpatterned fabrics are also shown in Figure 5.

In patterned fabrics, six different types of defects that usually appear in fabric texture are considered. These defects are shown in Figure 6. Detection results for patterned fabrics are also shown in Figure 6. Images are 8-bit gray scale images of size 256×256 . These images are also used in [23, 26]. The resolution of the camera used for these images is 200 dpi.

For detecting defects, different sizes of detection windows were tested and the size of 16×16 yielded the best results. In patterned fabrics the size of the repetitive unit is nearly 16×16 . As explained in Section 3.1, in order to estimate the probability of encountering different labels (0 to $P + 1$) accurately, the size of the detection windows should be large enough. It is also dependent to P . Increasing the size of the

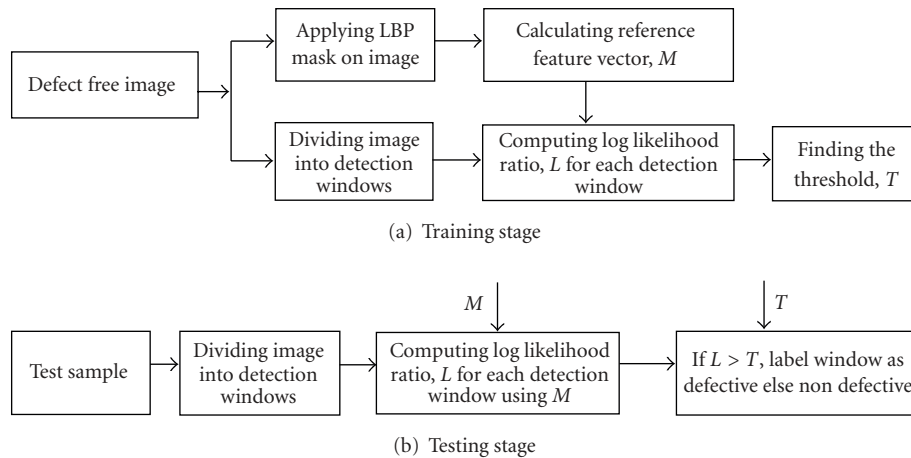


FIGURE 4: Overall block diagram of the proposed algorithm.

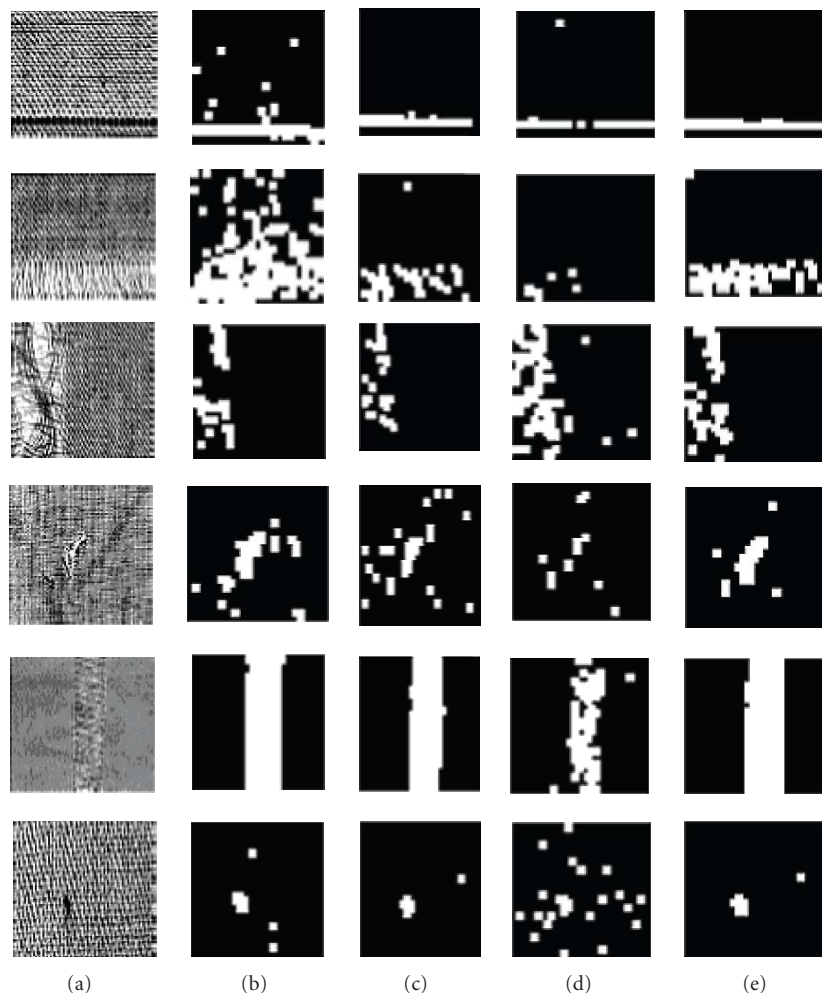


FIGURE 5: (a) Images of defective unpatterned fabrics from top to bottom: double yarn, missing yarn, broken fabric, weft crack, float, and knot. Detection results in the form of defect pattern using (b) $LBP_{8,3}$, (c) $LBP_{16,5}$, (d) $LBP_{24,7}$, and (e) $LBP_{8,3+16,5}$.

detection windows decreases the capability of the algorithm in detecting small size defects. Experimental results show that if there are at least 100 operators in each detection window, the probability of encountering different labels can be esti-

mated accurately. Since the maximum size of LBP mask in the proposed algorithm is 7×7 , the size of 16×16 for detection windows is sufficient for estimating these probabilities accurately.

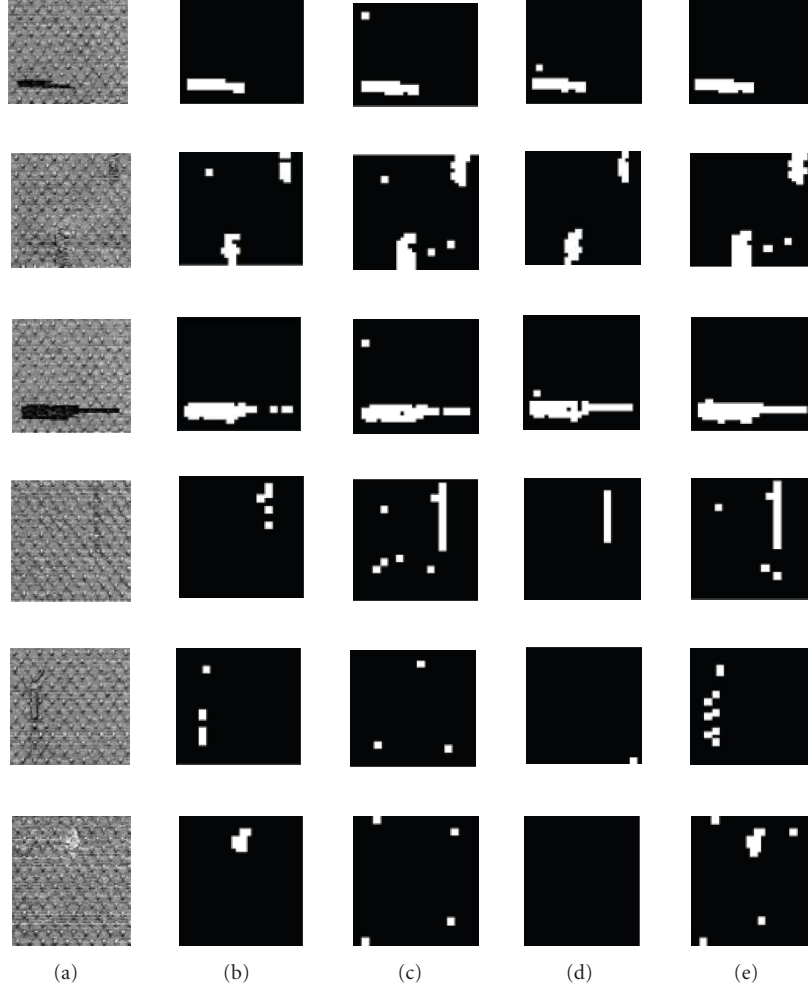


FIGURE 6: (a) Images of defective patterned fabrics from top to bottom: dirty yarn, hole, thick bar, broken end, netting multiple, knot. Detection results in the form of defect pattern using (b) $LBP_{8,3}$, (c) $LBP_{16,5}$, (d) $LBP_{24,7}$, and (e) $LBP_{8,3+16,5}$.

TABLE 1: Detection rate (%) for different defect types of patterned fabrics: (a) dirty yarn, (b) oil stain, (c) broken end, (d) netting multiple, (e) hole, and (f) knots.

Operator	P, w	Number of features	Defect types					
			(a)	(b)	(c)	(d)	(e)	(f)
$LBP_{P,w}$	8,3	10	97	95	95	92	96	95
	16,5	18	96	94	94	N.D ¹	95	N.D
	24,7	26	97	95	94	N.D	95	N.D
	8,3 + 16,5	10 + 18	98	98	98	95	96	95
	8,3 + 24,7	10 + 26	98	96	96	94	95	97
	16,5 + 24,7	18 + 26	97	95	94	N.D	95	N.D
	8,3 + 16,5 + 24,7	10 + 18 + 26	98	98	98	96	97	97

¹Not detected, when the number of detected defective windows is less than half of the number of true defective windows.

One of the ways to measure the performance of defect detection algorithms is calculating the detection rate [25] which is defined as follows:

$$DR = 100 \times \left(\frac{N_{cc} + N_{dd}}{N_{total}} \right), \quad (10)$$

where N_{cc} is the number of defect free windows which are detected as nondefective (true negative). N_{dd} is the number of defective windows which are detected as defective (true positive). N_{total} is the total number of detection windows that is created on the image. Table 1 illustrates the detection rate for different types of the defects using different LBP masks. For computing the detection rate, defect pattern generated

TABLE 2: Detection rate (%) for different defect types of unpatterned fabrics: (a) Double Yarn, (b) Missing Yarn, (c) Broken Fabric, (d) Weft Crack, (e) Float, and (f) Knots.

Operator	P, w	Number of features	Defect types					
			(a)	(b)	(c)	(d)	(e)	(f)
LBP $_{P,w}$	8,3	10	97	85	95	92	94	95
	16,5	18	98	90	93	90	94	93
	24,7	26	95	N.D	93	90	93	90
	8, 3 + 16, 5	10 + 18	98	98	98	95	97	97
	8, 3 + 24, 7	10 + 26	98	96	96	94	95	95
	16, 5 + 24, 7	18 + 26	97	N.D	94	92	95	94
	8, 3 + 16, 5 + 24, 7	10 + 18 + 26	99	98	98	96	97	97

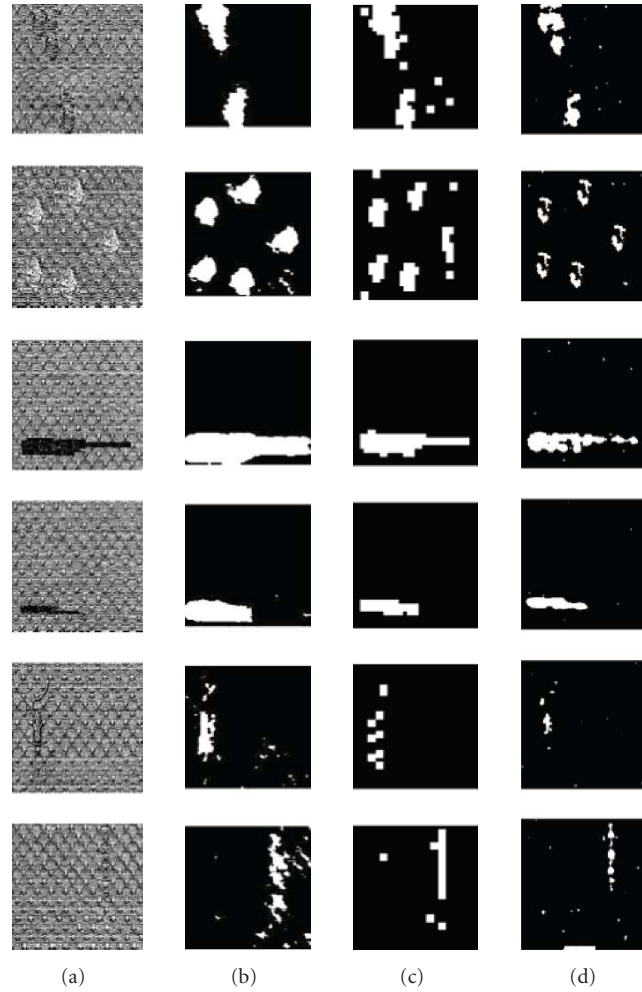


FIGURE 7: (a) Images of defective fabrics, (b) defect pattern generated by the method of [26], (c) defect pattern generated by proposed algorithm (overlapping step 8 pixels), and (d) defect pattern generated by proposed algorithm (overlapping step 15 pixels).

by the algorithm is divided into 16×16 windows and a window that contains at least one white pixel is considered as defective. Since images are of size 256×256 , N_{total} is 256. In our image dataset of patterned fabrics, there exist sixty images of dot patterned Jacquard fabrics. Half of these images are defect free. Training stage is done using only five samples of defect free images. In testing stage all of the defect free samples are classified correctly. On the other hand, for each

type of the defects there exist five different images in our data set. The detection rate listed in Table 1 is the average of the detection rates for all of the defective images in the database. In Table 2 detection rates for different types of the defects in unpatterned fabrics are listed.

As shown in Figures 5 and 6, a 3×3 mask for applying LBP operator, LBP $_{8,3}$, detects almost all kinds of the defects, but the defect pattern found for patterned fabrics is not

TABLE 3: Detection rate (%) of proposed algorithm and algorithm of [26] tested on dot patterned fabrics: (a) dirty yarn, (b) hole, (c) oil stain, (d) knot, (e) broken end, and (f) netting multiple.

Algorithm	Defect type						Average detection rate
	(a)	(b)	(c)	(d)	(e)	(f)	
Reference [26]	96	97	94	95	95	94	95.1
Proposed ¹	98	95	97	94	97	93	95.8
Proposed ²	98	96	98	94	98	95	96.5

¹Overlapping step 8 pixels.

²Overlapping step 15 pixels.

continuous and exact in unpatterned fabrics. Therefore, the features of 3×3 mask are combined with the features of 5×5 and 7×7 masks using (7). On the other hand, using 5×5 and 7×7 (LBP_{16,5} and LBP_{24,7}) masks for detection as illustrated in Table 1 do not detect defects like netting multiple and knots. Table 1 shows that combination of features of 3×3 and 5×5 masks (LBP_{8,3+16,5}) has an appropriate detection rate (more than 95%).

4.1. Performance comparison

In the subsequent subsections, the performance of the proposed algorithm is compared with the performance of similar algorithms. For performance comparison two criteria are used:

- (1) defect detection accuracy,
- (2) computational complexity and speed.

For comparing the detection accuracy of the algorithms, the defect patterns generated by different algorithms are compared visually. The detection rate is also used to compare the detection accuracy.

In order to compare the computational complexity, the number of operations required for processing a test sample is considered.

4.1.1. Patterned fabrics

In order to make a comparison between the proposed method and the existing methods for defect detection in patterned fabrics, the results of the proposed method are compared with the results of methods in [26, 27]. These methods are the two newest methods for detecting defects in patterned fabrics. In the training stage of the method of [26], a window of a defect free sample is selected. The size of this window should be greater than the size of the repeated part of fabric texture. This window will be moved on a defect free sample image pixel by pixel. At each point, difference between gray values of pixels in the window and gray values of pixels in the underlying window on the image is computed. The average of absolute value of differences is computed for each point. By defining a suitable threshold, defective points can be detected. Images of patterned fabrics in both methods are the same. Comparison of the results in Figure 7 reveals that in some specific types of the defects like knot and hole, the method of [26] yields more accurate defect pattern; and in some other types like dirty yarn, oil

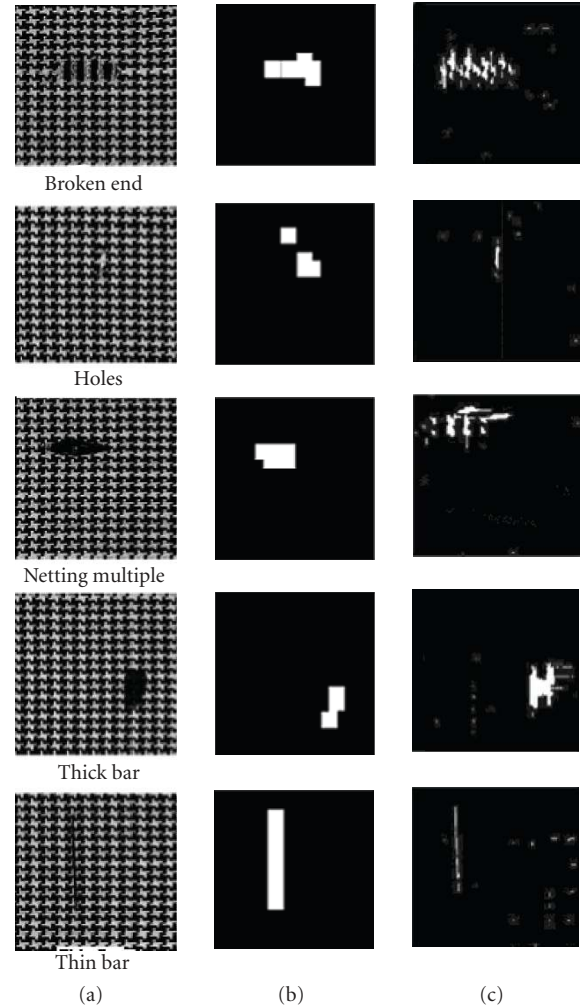


FIGURE 8: Detection results for star patterned fabrics: (a) defective samples, (b) detection results of the proposed algorithm, and (c) detection results of the method of [27].

stain, and broken end, the proposed method generates more accurate defect pattern. So, the proposed method and the method in [26] have almost the same accuracy. The method of [26] requires a large amount of computations and it is not suitable for online implementation. However, the proposed method due to its simplicity can be used for online defect detection. It should be noted that the resolution of the defect pattern generated by our proposed algorithm can

TABLE 4: Detection rate (%) of proposed algorithm and algorithm of [27] tested on star patterned fabrics: (a) thin bar (dirty yarn), (b) hole, (c) thick bar (oil stain), (d) broken end, and (e) netting multiple.

Algorithm	Defect type					Average detection rate
	(a)	(b)	(c)	(d)	(e)	
Reference [27]	95	95	94	93	96	94.6
Proposed ¹	97	97	96	98	96	96.8
Proposed ²	98	97	99	98	95	97.4

¹Overlapping step 12 pixels.²Overlapping step 24 pixels.

TABLE 5: Detection rate (%) of proposed algorithm and algorithm of [27] tested on box patterned fabrics: (a) thin bar (dirty yarn), (b) hole, (c) thick bar (oil stain), (d) broken end, and (e) netting multiple.

Algorithm	Defect type					Average detection rate
	(a)	(b)	(c)	(d)	(e)	
Reference [27]	95	97	94	94	94	94.8
Proposed ¹	97	96	98	98	95	96.8
Proposed ²	98	96	98	98	98	97.6

¹Overlapping step 12 pixels.²Overlapping step 24 pixels.

be increased by increasing the overlapping of the detection windows. Moving windows pixel by pixel on the image will generate a defect pattern like those in [26]. It is shown in the fourth column of Figure 7. However, increasing the overlapping between detection windows will increase the complexity of the algorithm. Table 3 illustrates the detection rate computed for our proposed algorithm and algorithm of [26]. The method of [27] uses Bollinger bands for detecting defects in patterned fabrics. Bollinger bands consist of three bands: upper, middle, and lower. In this method, patterned fabrics can be considered as comprising many rows (columns), with a pattern designed on each row (column). The principle of this method is that the patterned rows (columns) will generate periodic upper and lower bands. Any defect region in patterned fabric means that there would be a break of periodicity in the pattern. For better evaluation performance of the proposed algorithm, it has been tested on two other types of patterned fabrics named as star patterned and box patterned. Detection results of the proposed algorithm and method of [27] are compared in Figures 8 and 9. The size of a repetitive unit for both fabrics is 25×25 . Therefore, the size of 25×25 is selected for detection windows. The overlapping step is 12 pixels. Tables 4 and 5 illustrate the detection rate of the proposed algorithm and algorithm of [27] tested on star patterned and box patterned fabrics. In the method of [26] if the size of repetitive unit of fabric texture is 16×16 and the size of test sample is 256×256 pixel, moving the detection windows on test sample pixel by pixel yields 58 081 different positions. For each position of detection window in this method, 256 subtractions, 255 additions, 256 comparisons, and one division are required. Therefore, processing a test sample of size 256×256 pixel by this method requires 14 868 736 subtractions, 14 810 655 additions, 14 868 736 comparisons, and 58 081 divisions.

In the proposed method if overlapping step between detection windows is 8 pixels, total number of detection

windows will be 961. In each detection window, for applying $LBP_{8,3}$, 1568 comparisons, 10 multiplications, and 10 divisions are required. For applying $LBP_{16,5}$, 2304 comparisons, 18 multiplications, and 18 divisions are required. Therefore, to process a test sample by the proposed method ($LBP_{16,5+8,3}$), 3 720 992 comparisons, 26 098 multiplications, and 26 098 divisions are required.

It should be noted that for computing log-likelihood ratio, the $\log(\cdot)$ operation can be omitted and approximated log-likelihood ratio can be used. In approximated log-likelihood ratio, $\log(x)$ is approximated as $x - 1$ so approximated log-likelihood ratio (\hat{L}) can be computed by

$$\begin{aligned}
 L(S, K) &= \sum_{i=0}^{P+1} S_i \log \left(\frac{S_i}{M_{iK}} \right) \approx \sum_{i=0}^{P+1} S_i \left(\frac{S_i}{M_{iK}} - 1 \right) \\
 &= \sum_{i=0}^{P+1} \frac{S_i^2}{M_{iK}} - \sum_{i=0}^{P+1} S_i = \sum_{i=0}^{P+1} \left(\frac{S_i^2}{M_{iK}} \right) - 1 \quad (11) \\
 \hat{L}(S, K) &= \sum_{i=0}^{P+1} \frac{S_i^2}{M_{iK}}.
 \end{aligned}$$

Simulation results show that using approximated log-likelihood ratio does not change the detection rate of the proposed algorithm.

In the method of [27] if the size of repetitive unit of fabric texture is 25×25 in each row (column) of the test sample of size 256×256 , 232 segments of length 25 pixels can be considered. In each segment, 48 additions, 25 subtractions, 25 multiplications, 2 divisions, and one square root are required. Table 6 illustrates the number of operations which are required for processing a test sample of size 256×256 , using proposed method and methods of [26, 27].

As shown the computational complexity of the proposed algorithm can be reduced by reducing the overlapping step between detection windows and reducing the resolution of

TABLE 6: Number of different operations which are required to process a test sample using different algorithms.

Algorithm	Size of repetitive unit of fabric texture	Addition	subtraction	Multiplication	comparison	division	Square root
Proposed ¹	16×16	23064	0	26098	3720992	26098	0
Proposed ²	25×25	8424	0	9072	3657312	9072	0
[26]	16×16	14810655	14868736	0	14868736	58081	0
[26]	25×25	33586176	33640000	0	33640000	53824	0
[27]	16×16	3701760	1974272	1974272	0	123392	123392
[27]	25×25	5701632	2969600	2969600	0	118784	118784

¹Overlapping step of 8 pixels between detection windows.

²Overlapping step of 12 pixels between detection windows.

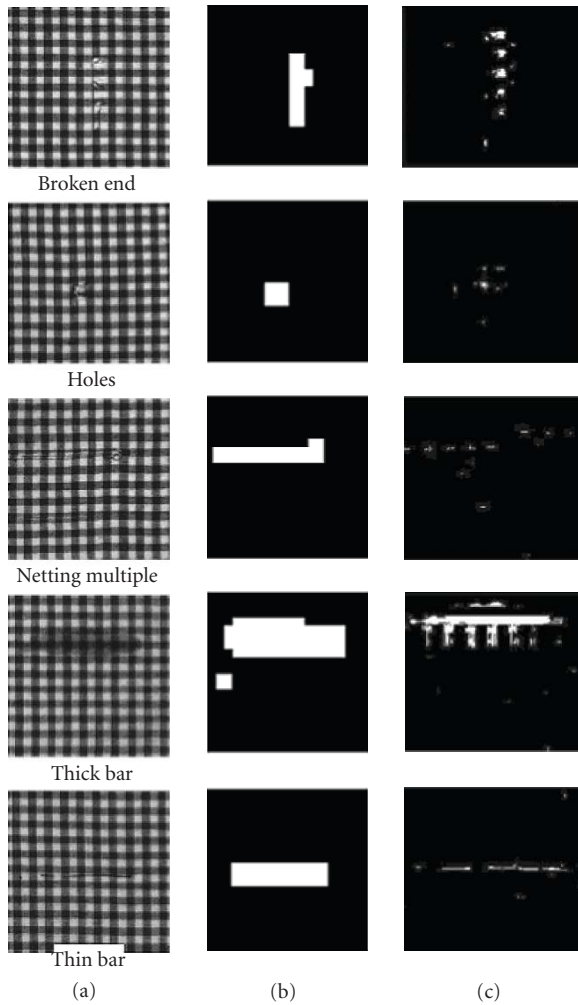


FIGURE 9: Detection results for box patterned fabrics: (a) defective samples, (b) detection results of the proposed algorithm, and (c) detection results of the method of [27].

the defect pattern, which cannot be done in similar algorithms.

4.1.2. Unpatterned fabrics

For evaluating performance of the algorithm in detecting defects of unpatterned fabrics, the detection results of the pro-

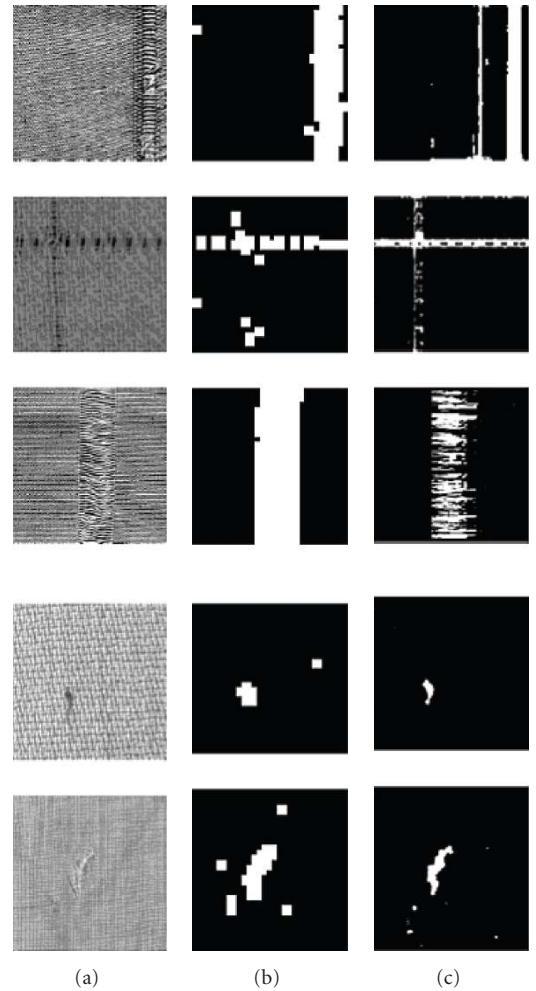


FIGURE 10: (a) Defective fabric images, (b) detection results using our proposed algorithm, and (c) detection results using Gabor filters.

posed algorithm are compared with those of the defect detection using Gabor filters [28]. Defect detection using Gabor filters is one of the most accurate methods [29]. In this method [28], an image of a defect free sample is passed through a bank of Gabor filters. Transfer function of each filter is obtained by changing scale and orientation of the Gabor functions. In the method selected for comparison, there

exist 16 filters in the filter bank, which are obtained by changing the orientation and scale of Gabor functions to four orientations and four scales. Output of each filter is thresholded and combined with the output of the other filters using an image fusion technique. So, for each filter in the filter bank, a set of suitable parameters are computed. Passing test sample through these filters will generate a defect pattern that detects and localizes the irregularities in fabric texture. Figure 10 illustrates the detection results of the proposed algorithm and the detection results using Gabor filters. Some of the images of unpatterned fabrics were scanned from album of standard defects in textile industry [30] and the others were collected from textile mills around TamilNadu state of India. These images are gray-scale images with 8 bits long and with the size of 256×256 . If we use a procedure for computing detection rate like what was used for patterned fabrics, the average detection rate for proposed algorithm will be 97.1% and for Gabor filters will be 98%. The methods that have been based on Gabor filters use the idea of multichannel filtering which takes a lot of time. Therefore, these methods have a little chance for online implementation.

5. CONCLUSION

In this paper, a new method for detecting textural defects in fabrics based on modified local binary patterns has been presented. The proposed method has an acceptable detection rate (more than 95%) in all kinds of the defects which is more than that of human experts in both unpatterned and patterned fabrics. Furthermore, detecting all kinds of the defects needs considering different windows which can be easily done using the multiresolution property of this method.

This method is a useful tool for textile industries to inspect, identify, and localize local defects in textile products. The proposed method is simple, gray-scale invariant, and multiresolution. According to the performance comparison and implementation results, it is evident that the proposed method can detect and localize defects in patterned fabrics, more accurately than similar algorithms. The computational complexity of the proposed algorithm is less than similar algorithms. Therefore, it can be used in online defect detection.

In spite of low-resolution defect pattern, the defect pattern generated by the proposed method is suitable for a wide range of the defects. It should be mentioned that, practically, the detection rate and detection speed are of higher privilege than the resolution of the defect pattern generated by the algorithm.

The proposed method is implemented on three types of patterned fabrics: dot patterned, box patterned, star patterned and two types of unpatterned fabrics: twill and plain. Six different types of patterned fabric defects and six different types of unpatterned fabrics are considered in this research. Implementation results show that the proposed method is capable of detecting all kinds of the defects in both types of the fabrics. It should be noted that this method can be used for defect identification too. It can also be used for defect detection in products which have regular and periodic textures such as timber or plastic.

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