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A Fabric Defect Detection Algorithm via Context-based Local Texture Saliency Analysis

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Abstract— **This paper considers the problem of fabric defect detection based on context-awareness and local texture saliency, where the techniques of LBP (Local Binary Pattern), salient region detection and segmentation based on optimal threshold are employed. In the proposed algorithm, a target image is first divided into blocks, then the LBP technique is used to extract the texture features of blocks. Second, for a given image block, several other blocks are randomly chosen for calculating the LBP contrast between a given block and the randomly-chosen blocks. Based on the obtained contrast information, a saliency map is produced. Finally, saliency map is segmented by using an optimal threshold, which is obtained by an iterative approach. Through these procedures, detection result is obtained. The proposed algorithm integrates the local texture features and the whole image texture information. The experimental results show that the proposed algorithm, integrating local texture features and global image texture information, can detect texture defects effectively.**

Index Terms— **random saliency detection, fabric defects detection**

I. Introduction

FABRIC defect detection plays an important role in textile quality control. Currently, fabric defect detection algorithms are mainly divided into the following three categories: (1) model approaches (2) spectrum approaches and (3) statistical approaches.

Among them, model approaches extract image texture features through modelling and parameter estimation methods [1]. Model approaches usually share a high computational complexity, but their detection results are not very satisfying.

Spectrum approaches first transform texture images to the spectrum domain and then apply some energy criterion for image feature extraction. Their performance heavily depends on the chosen filter [2].

Statistical approaches [3], employing different statistical properties of image background and defects on texture and/or image intensity etc, can effectively and conveniently detect fabric defects, and therefore have been extensively researched. But different statistic approaches on image texture and intensity have a significant influence on the the detection results.

Among statistical approaches, Local Binary Pattern (LBP) [4] is an effective texture feature extractor and has been widely used in texture classification, image retrieval and face image analysis, etc, in the last decade.

Recently, LBP has also been applied for fabric defect detection [5]–[7]. For example, Tajeripour et al [5] employed the property difference between the LBP features of a given fabric image and a reference image for defect detection. For different types of fabric, this method needs different reference images. The selection of reference images has a significant influence on the detection accuracy. In Refs [6], [7], the techniques of LBP and SVM (Support Vector Machine) are proposed for defect detection. The proposed methods use the main pattern set of normal fabric images without defects and the set of fabric images with defects to train a SVM classifier, which was reported of having achieved a high detection accuracy. However, this method requires different types of training set for different fabric images and has a poor adaptability.

The methods based on saliency analysis are inspired by the mechanism of human visual perception and can quickly search for the salient areas or a target in a given image without any priori knowledge. For example, Geforman et al [8] and Huang et al [9] proposed the methods based on the context-based saliency analysis for target detection in natural scene images and achieved some satisfactory results.

This paper proposes a novel fabric defect detection algorithm considering the global saliency of image context and the LBP features. First, the target image is divided into blocks, then LBP operator is used to produce the texture features of the obtained image blocks. Second, for a given image block, several other image blocks are randomly chosen for calculating the LBP contrast. Then, based on the contrast information, a saliency map is produced. Third, the optimal threshold is obtained via an iterative approach and used to segment the saliency map. Finally, the segmentation of the saliency map gives the fabric defects. The proposed method doesn't need training process and our experimental results show that the proposed method yields an impressive detection accuracy.

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II. Local Binary Pattern (LBP)

The LBP operator regards a neighborhood of a given pixel as a processing unit. If the grayscale of a neighboring pixel is larger than the gray scale of the given pixel, the LBP value of the neighboring pixel is set to 1, otherwise 0. Then we get a binary sequence in the clockwise direction. The binary sequence is then transformed into its decimal version, which is set as the feature value of the given pixel. More specifically, the LBP value of a given pixel is given as follows.

$$\begin{cases} LBP_{P,R} = \sum_{i=0}^{P-1} s(g_i - g_c) \times 2^i \\ s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \end{cases} \tag{1}$$

where g_c is the gray value of the central pixel and g_i the gray value of its i-th neighbor. R defines the size of the neighborhood and P is the number of neighboring pixels in the neighborhood.

The LBP operator can capture the structural and statistical features of a given image and therefore the LBP feature histogram effectively characterizes the image texture information.

If the given image is rotated, then the binary sequence changes. For example, a binary sequence 11011101 might change to 01110111. Thus, although two image blocks share similar textures and local structure, their LBP value could be significantly different.

In order to make the LBP operator in Equation (1) rotation-invariant, in Ref [4], the basic LBP binary sequence is consecutively rotated $P-1$ times, among the P binary sequences, the one with the minimum decimal value is chosen as the rotation-invariant LBP sequence. For example, the rotation-invariant versions of sequences 11011001 and 01110110 are both 00111011, which means the two corresponding local neighbors share the same LBP features.

More mathematically, the rotation-invariant LBP value is given as follows.

$$LBP_{P,R}^{ri} = \min\{ROR(LBP_{P,R}, i)|\ i = 0, \cdots, p-1\} \tag{2}$$

where ROR is the binary sequence rotation operator. $ROR(LBP_{P,R}, i)$ first cyclic shifts i times the binary value of $LBP_{P,R}$, then transforms the shifted binary sequence to its decimal value. The corresponding LBP pattern is denoted by ri.

One of the modified LBP operator is known as "uniform pattern". Based on extensive experiments and statistics, the authors of literature [4] concluded that among all binary LBP sequences, the sequences with the mutation number from binary "0" to "1" or "1" to "0" not larger than 2 account for the majority. These majority ones are called "uniform patterns" in [4]. The LBP value of the "uniform pattern" is calculated by the primitive LBP operator.

The number of the minority patterns (non-unform patterns) are $P(P-1)+3$. For a circle sampling area with P sampling points, the pattern number is reduced from 2^P to $P(P-1)+3$. For texture images, most patterns belongs to uniform patterns, thus, calculating the histogram of these patterns can effectively extract the textural features. This pattern is denoted by $u2$ and the LBP values is given as follows.

Thus, the modified pattern can effective extract the texture features of a given image with a reduced feature dimensionality. The modified pattern is denoted by $u2$, and the modified LBP value is given as follows.

$$LBP_{P,R}^{u2} = \begin{cases} \sum_{i=0}^{P-1} s(g_i - g_c) \times 2^i, & U \leq 2 \\ P(P+1)+3, & \text{otherwise} \end{cases} \tag{3}$$

where U is the mutation number of 1 to 0 or 0 to 1 in a target binary sequence.

Another modified LBP operator is the rotation-invariant uniform pattern, which is a combination of the rotation-invariant pattern and uniform pattern and denoted by $riu2$. The LBP value of rotation-invariant uniform pattern is given as follows.

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{i=0}^{P-1} s(g_i - g_c) \times 2^i, & U \leq 2 \\ P(P+1)+3, & \text{otherwise} \end{cases} \tag{4}$$

The number of this pattern is reduced from 2^P to $P+2$.

III. Context-based saliency analysis

The context-based saliency analysis contends that the saliency of a given pixel is related to or represented by the image block centered at this pixel. If the difference between the image block centered at pixel i to other image blocks is significant, then pixel i is salient. If a image has N image blocks and image block B_i is the target block, the other $N-1$ block are candidates as its comparisons. Usually, a higher detection accuracy means the need of more comparison blocks, which also brings a higher computational complexity. With a guaranteed detection accuracy, how to effectively reduce the computational complexity is a key point to consider. Geferman et al [8] chose the rest $N-1$ blocks to compare with a target block and then selected K ($K < N-1$) the most similar blocks to calculate the saliency of the centered pixel. This strategy needs the highest computational cost. Huang et al [9] randomly chose $2K$ ($2K < N-1$) images for comparison and kept the most similar K blocks for calculating the saliency of the centered pixel, with a reduced computational cost compared with the previous one.

Since the defect regions of a fabric image only account for a very small fraction of the entire image, the event that a randomly-chosen image block from the $N-1$ candidates comes from the background of the image has a very high probability. This means that most randomly-chosen image blocks are similar. Thus, considering the characteristics of fabric images, we randomly choose K image blocks for calculating the their similarities to a target image block. Block similarity defines pixel saliency and gives final visual saliency map.

Our context-based saliency analysis can be summarized as follows.

(1) Randomly choose location p_i of (image block B_i) as follows.

$$p_j = \mathrm{round}(p_i + \omega R_j) \tag{5}$$

where $j = 1, \cdots, K$, R_j is a uniform distributed variate and $R_j \in [-1, 1] \times [-1, 1]$, ω is set as the half of the width and height scales of the target image.

(2) Calculate the feature distance between image blocks. Let $d_f(B_i, B_j)$ denote the LBP feature distance between the locations of image blocks B_i and B_j. If $d(B_i, B_j)$ is large for any image block B_j, then block B_i is salient. Distance $d(B_i, B_j)$ is given as follows.

$$d(p_i, p_j) = \frac{d_f(p_i, p_j)}{1 + C \times d_p(p_i, p_j)} \tag{6}$$

where C is a ratio coefficient and $C \in [0, 1]$.

(3) Calculate the saliency s of the target image block i as follows.

$$s_i = 1 - \exp\left(-\frac{1}{K}\sum_{k=1}^{K} d(p_i, p_k)\right) \tag{7}$$

IV. Segmentation by optimal threshold

When the saliency map is obtained, following is an image segmentation via an optimal threshold obtained through iterations to detect and localize the fabric defects. First, the saliency map is segmented into two parts of defects and background. Then the mean grayscales of the two parts are respectively computed. The average of the two means is taken as an updated threshold to iteratively segment the saliency map until the the process converges.

To be more specific, the process is summarized as follows.

(1) Initialize the threshold T_0 ($k = 0$) by

$$T_0 = \frac{Z_{\min} + Z_{\max}}{2} \tag{8}$$

where $Z_{\min}$ and $Z_{\max}$ is respectively the minimum and the maximum grayscale of the obtained saliency map.

(2) Classify the grayscales via threshold T_k ($k = 0, 1, \cdots$) to two parts of R_1 and R_2.

$$\begin{cases} R_1 = \{f(i,j) |\ f(i,j) \geq T_k\} \\ R_2 = \{f(i,j) |\ 0 \leq f(i,j) < T_k\} \end{cases} \tag{9}$$

where $f(i, j)$ is the grayscale of pixel (i, j).

(3) Calculate the mean grayscales of R_1 and R_2.

$$\begin{cases} Z_1 = \dfrac{\sum_{f(i,j) \geq T_k} f(i,j) N(i,j)}{\sum_{f(i,j) \geq T_k} N(i,j)} \\ Z_2 = \dfrac{\sum_{0 \leq f(i,j) < T_k} f(i,j) N(i,j)}{\sum_{0 \leq f(i,j) < T_k} N(i,j)} \end{cases} \tag{10}$$

(4) Update threshold T_{k+1}

$$T_{k+1} = \frac{Z_1 + Z_2}{2} \tag{11}$$

(5) If $|T_{k+1} - T_k| < \delta$ (δ is a predetermined small value), end the iteration, otherwise go to Step (2).

(6) Segment the saliency map via the obtained thresh to two parts of defects and background.

V. Algorithm

Based on the above mentioned discussions, a novel fabric defect detection algorithm via context-based local texture saliency analysis is proposed. The algorithm comprises four parts including (a) image blocking, (b) LBP feature extraction, (c) context-based saliency analysis and (d) iterative thresholding.

(1) Image blocking: Divide image I of the size $M \times N$ to blocks B_i of size $m \times m$ for all $i = 1, \cdots, N_b$ (N_b is the image block number). Since one block corresponds to a pixel of the produced saliency map, in order to improve the resolution of saliency, blocks $f_1, \cdots, f_{N_b}$ have some overlaps to each other. The size of overlapping region is $m \times c$ or $c \times m$. The more overlapping regions, the higher saliency resolution but with a increased computational cost.

(2) For a target block B_i, randomly choose K other blocks according to the strategy discussed in Section III.

(3) Calculate the LBP features of block B_i and the K randomly chosen blocks B_j ($j = 1, \cdots, K$).

(4) Calculate the LBP feature distances between B_i and B_j ($j = 1, \cdots, K$). Since the LBP features are represented by histogram, we use the chi-square function to measure the LBP feature distances, which are given as follows.

$$d_f(B_i, B_j) \doteq \chi^2_{i,j}(B_i, B_j) = \sum_{t=1}^{T} \frac{(V_{i,t} - V_{j,t})^2}{V_{i,t} - V_{j,t}} \tag{12}$$

where T is the feature dimension, $V_{i,t}$ is the t-th entry of the feature vector of B_i and $V_{j,t}$ is the t-th entry of the feature vector of B_j.

(5) Calculate the Euclidean distances $d(B_i, B_j)$ between the locations of f_i and f_j for all $j = 1, \cdots, K$.

(6) Calculate the saliency value s_i of block B_i as in Equations (6) and (7), and therefore obtain the final saliency map S.

(7) Denoise S to obtain m as follows.

$$m = g * (S \circ S) \tag{13}$$

where g is the radius of the circular smoothing filter and "$\circ$" denotes the Hadamard inner product operator and "$*$" the convolution operator.

(8) Transform the saliency map to a grayscale image Gm with the intensities in $\{0, \cdots, 255\}$ as follows.

$$Gm = \frac{m - \min(m)}{\max(m) - \min(m)} \times 255 \tag{14}$$

where $\min(m)$ denotes the minimum grayscale of matrix m and $\max(m)$ the maximum grayscale of matrix m.

(9) Segment Gm by the obtained optimal threshold and separate defects from background.

VI. EXPERIMENTS AND ANALYSIS

To evaluate the performance of the proposed algorithm, we choose several types of defect image (including “fuzzyball”, “wrong draw”, “mispick”, “overshot” etc) from an image dataset for our experiments. Image size is 512×512. The experimental images are shown in the first row of Figure 1.

We first analyse the influences of LBP operator, image block size, random image block number K on saliency map and then compare ours with the existing visual saliency models and finally give the segmentation result by optimal thresholding.

First, for the investigation of the influence of different LBP operators on saliency map, we set image size as 16×16, $K = 20$ and overlapping size as 16×8. (1) The saliency maps produced by primitive LBP operator with the sampling radius $r = 1$ and the sampling point number $P = 8$ and the feature dimension equal to 256 are given in the second row in Figure 1. (2) The saliency maps by primitive LBP operator with $r = 3$, $P = 8$ and the feature dimension equal to 256 are given in the third row in Figure 1. (3) The saliency maps by “uniform pattern” LBP operator with the feature dimension equal to 59 are given in the fourth row in Figure 1. (4) The fifth row in Figure 1 shows the saliency maps produced by the rotation-invariant uniform pattern $riu2$ operator with the feature dimension equal to 10.

From Figure 1, it is not difficult to see that the saliency maps produced by the primitive operator with $r = 1$ and $P = 8$ and the $u2$ operator are better than those produced by the primitive operator with $r = 3$ and $P = 8$ and the $riu2$ operator.

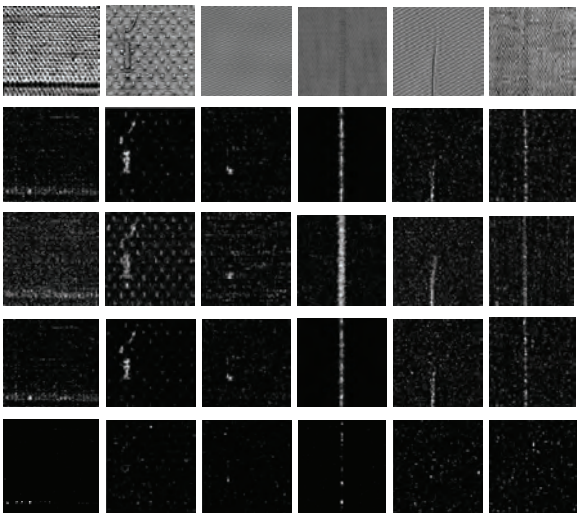

Figure 1. Experimental Fabric images and the saliency maps produced by different LBP operators. First row: original raw images; Second row: saliency maps produced by primitive LBP operator ($r = 1, p = 8$); Third row: saliency maps produced by primitive LBP operator ($r = 3, p = 8$); Fourth row: saliency maps produced by enhanced the $u2$ LBP operator; Fifth row: saliency maps produced by enhanced the $riu2$ LBP operator;

The feature dimension used by the $u2$ operator is 59, much less than that used by the primitive operator with $r = 1$, $P = 8$, (i.e., 259 dimensional). Thus, the $u2$ operator is more of computational efficiency.

We use the $u2$ operator in our following experiments for feature extraction.

Next, we show the influence of image block size on the saliency maps. The number of random image block K is set to 20. (1) In Figure 2, the first row shows the saliency maps generated by 8×8 pixel image blocks with the overlapping size equal to 8×4 pixels. (2) The second row shows the saliency maps generated by 12×12 pixel image blocks and the overlapping size is 12×6. (3) The third row shows the saliency maps generated by 16×16 pixel image blocks and the overlapping size is 16×8. (4) The saliency maps generated by 20×20 pixel image blocks is shown in the fourth row and the overlapping size is 20×10. It can be seen from Figure 2, with the increase of image block size, the contrast degree of the obtained saliency maps is noticeably increased. The reason is that when the image block size is small, the extracted LBP features can not effectively characterize the properties of the given image block. When the block size increases, the characterization ability of the LBP features also increases. But when the block size reaches to 20×220, some detail information of defect region is lost, because when block size is large and defect region is small, LBP operator can not effectively capture the information of defects. Thus, we set the block size to 16×16.

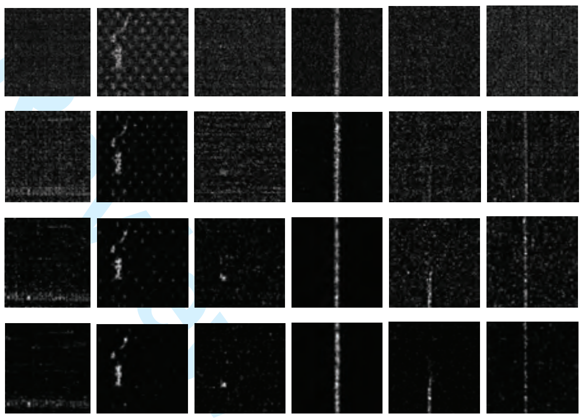

Figure 2. Influence of image block size on saliency map. First row: saliency maps generated by 8×8 pixel blocks; Second row: saliency maps generated by 12×12 pixel blocks; Third row: saliency maps generated by 16×16 pixel blocks; Fourth row: saliency maps generated by 20×20 pixel blocks;

After that, we investigate the influence of K (the number of image blocks) on saliency maps. We use $u2$ LBP operator for feature extraction. The image block size is 16×16. (1) When $K = 10$, the obtained saliency maps are given in the first row of Figure 3. (2) When $K = 20$, the obtained saliency maps are given in the second row of Figure 3. (2) When $K = 30$, the obtained saliency maps are given in the third row of Figure 3. Theoretically, a larger K produces a better saliency map but on the cost of a higher computational complexity. From Figure 3, it can be seen that when $K = 10$, the quality of the obtained saliency map is not good. When

$K = 20$ and $K = 30$, the quality of the saliency maps is better, but from $K = 20$ to $K = 30$, the increase of the saliency maps is not significantly noticeable. Trading off between the increased computational complexity and the quality of saliency maps, we set $K = 20$ in our following experiments.

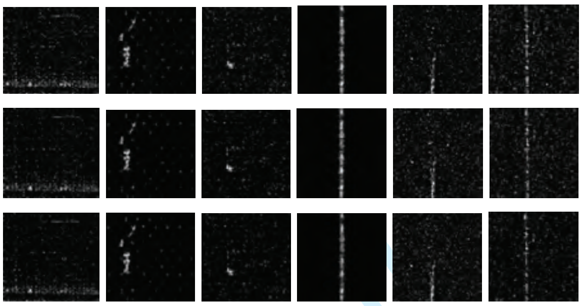

Figure 3. Influence of image block number K on saliency map. First row: saliency maps with $K = 10$; Second row: saliency maps with $K = 20$; Third row: saliency maps with $K = 30$;

Through extensive experiments and analysis, we find that when the block size is set to 16×16, $K = 2$ and $u2$ LBP operator is employed, the quality of the saliency maps is the best.

Following, we compare the saliency maps by the proposed algorithm and that those by other visual saliency models. The comparison results are given in Figure 4.

In Figure 4, the first row shows the saliency maps generated by the residual spectrum method [10]. The second row shows the saliency maps generated by the random detection method [9]. The third row shows the saliency maps generated by the context-ware method [8]. The saliency maps by our method are given in the fourth rows with the corresponding segmentation results given in the fifth row.

It can be seen from Figure 4 that the saliency maps of fabric images, generated by the residual spectrum method and the random detection method, are not satisfactory since both of them merely consider the global information of fabric images but omit the local texture information. The context-ware method considers some context information when comparing block features and achieves better results on the 2nd to the 6th images (third row, from left to right). But its result on the first image (third row) is mediocre with a low efficiency when comparing with the results by other algorithms.

Our method consider the properties of fabric images and the context-base local texture features. The saliency maps generated by our method make the defect regions more prominent. When comparing with other image blocks, our method considers only a moderate number of image blocks and thus has a relatively high efficiency.

Finally, a segmentation of saliency map by the described optimal threshold can localize defect regions. The fourth row of Figure 4 shows the the finally correctly detected defects.

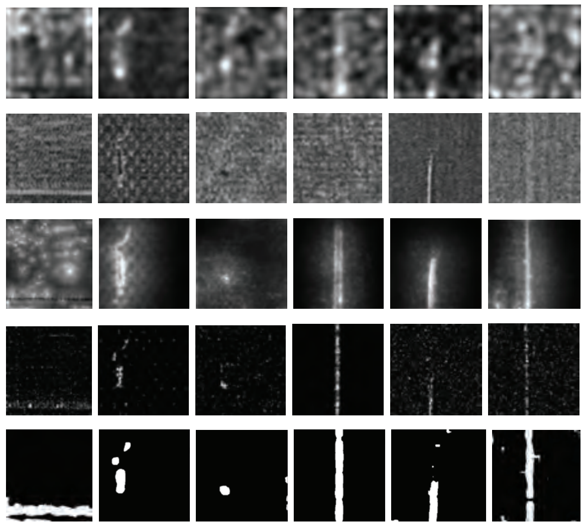

Figure 4. Comparison of the saliency maps by our algorithms and other methods and the final segmentation results by our method. First row: saliency maps by the residual spectrum method [10]; Second row: saliency maps by the random detection method [9]; Third row: saliency maps by the context-ware method [8]; Fourth row: saliency maps by our method; Fifth row: segmentation results by our method;

VII. Conclusion

In this paper, a novel fabric defect detection algorithm via context-based local texture saliency analysis is proposed. Given a target image, first the image is divided to several image blocks. Then, the LBP contrasts of each image block and other K randomly chosen image blocks are calculated. After that, a saliency map is generated. Next, through an iterative approach, a optimal threshold is obtained and used to segment the saliency map. The segmentation localizes the defects and gives the final detection result.

Our experiments show the influences of LBP operator, image block size and the number of random image block K on the generated saliency map. Via our experiments, we choose the optimal parameters for generating saliency map and therefore giving the final detection result. The generated saliency maps are compared with those generated by existing visual saliency model. Experiments show that the proposed algorithm can produce the saliency map with good quality and satisfactory efficiency. Using the obtained saliency map, the threshold by our proposed method can effectively separate defect regions. The proposed algorithm can also be tailored for a wide range of applications such as defect detection of glass surface, rail surface, etc.

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