Fabric Defect Detection Using Auto-Correlation Function

Elham Hoseini, Farnoush Farhadi, and Farshad Tajeripour

Abstract—**This paper introduces a new fabric segmentation approach for detecting fabric defects using auto-correlation function. This proposed approach consists of 4 steps: 1) calculating the texture primitive template by auto-correlation function from defect free fabric image in train phase, 2) enhancing the defect areas, through calculation the difference between each texture primitive template and texture image, 3) constructing the mean image to reduce high frequent information of background image, and 4) compute a perfect automatic threshold to present a binary image as a defect pattern.**

At the end of paper, validity and robustness of the new approach were proved by some experiments done on different defect types. The results indicate that proposed method is implementable on both patterned and unpatterned fabrics.

Index Terms—**Texture primitive template, defect pattern, image enhancement, defect segmentation.**

I. Introduction

Fabric defect detection is one of the most important phases in fabric production and is necessary to improve fabric quality. Methods to bring forward this, must involve approaches to increase accuracy meanwhile, reduce complexity and cost.

Nowadays, defect detections and fabric inspections are done by human experts and inspectors which show high cost and low performance and efficiency. They can detect at most 80% of fabric defects [1].

The width of fabrics, are usually between 1 and 3 meters and the speed of production line is in the range of 20 to 200 meters per minute. When the width is more than 2 meters and the speed of production line is more than 30 meters per minute, the human experts could only detect 60% of defects. It could be said obviously that fabric defect detection based on automatic approaches improves accuracy and efficiency of product line and enhance the produced fabric quality.

According to image processing and template detection techniques, fabric defect detection is categorized into two groups, as same as texture classification: intensity defects and geometrical defects. Former causes changes in gray level intensity values significantly and later rather than changing the gray levels, spoils the spatial correlation between pixels at defected areas.

Many researchers have accomplished effective activities to establish operative methods for segmenting defected images. For instances, Tajeripour applied local binary templates to detect the texture defects in patterned and unpatterned fabrics [2]. Sari-Sarraf [3], used adopting wavelet transforms and edge fusion to enhance the defected images. Cho et al [1], caused finding an threshold interval by using statistical analysis of gray level distributions range of the defect free image and also, Abouelela et al's approach [4], is based on using zero-mean and median smoothed image processing to enhance the defect image and diminish the background image, then segmenting the defects areas through a threshold based on a local variance of enhanced image.

This paper is organized as follows: in section 2, defect segmentation algorithm will be explained. In section 3 validity and robustness of the proposed algorithm will be discussed, and in section 4, conclusion will be finally presented.

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The authors are with the Department of Computer sciences and Engineering, Shiraz University, Iran (e-mail: ehoseini@cse.shirazu.ac.ir farnoush.farhadi@ gmail.com, tajeri@ shirazu.ac.ir).

II. Defect Segmentation Algorithm

Fig. 1. shows auto-correlation function curves of a periodic texture and the primitive texture is included of two vertical and horizontal periodicity along the X and Y axes. In defect free images, there is no difference between gray values of the pixels and gray level in texture primitive. In contrast, it could be seen an enormous difference in both intensity and geometrical defects and another strike change involves the gray values of the pixels in comparison to what was gain in defect free fabric.

Based on this, the new approach presented in this paper consists of 4 steps: computing the texture primitive template, enhancing the defected area, constructing the mean image and segmenting this by an Otsu's threshold approach. Figure (2) illustrates the algorithm and results. On the basis of this method, the introduced defect template behaves as a binary image which the black background demonstrate defect free texture and white regions indicate local and shape of defect zones in fabric texture.

A. Calculating Texture Primitive Template

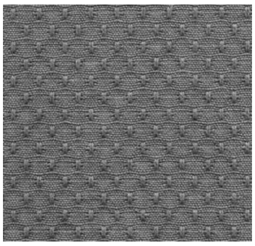
Fabric image has a periodic texture. This image is made of patterned rows and columns which are repeated along the image of the fabric according to the size of repetitive unit of fabric texture. Auto-correlation function is used to calculate size of repetitive unit (size of texture primitive template). Equation (1) shows auto-correlation function of vertical and horizontal images.

$$C_{x,0} = \frac{\frac{1}{M*(N-x)}\sum_{i=1}^{N-x}\sum_{j=1}^{M} G_{i,j} * G_{i+x,j}}{\frac{1}{M*N}\sum_{i=1}^{N}\sum_{j=1}^{M} {G_{i,j}}^2} \quad (1)$$

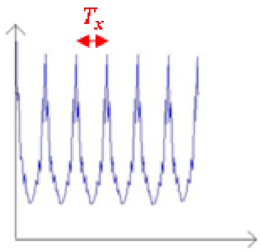
$$C_{0,y} = \frac{\frac{1}{N*(M-y)}\sum_{i=1}^{N}\sum_{j=1}^{M-y} G_{i,j} * G_{i,j+y}}{\frac{1}{M*N}\sum_{i=1}^{N}\sum_{j=1}^{M} {G_{i,j}}^2} \quad (2)$$

In above formulas, $M \times N$ is size of original defect free image in train phase, $G_{i,j}$ is gray value of pixel (i,j), $C_{x,0}$ and $C_{0,y}$ are auto-correlation values of axes X and Y, respectively. In Fig. 1. T_x and T_y, periodicity of the vertical and horizontal directions, give size of the texture primitive.

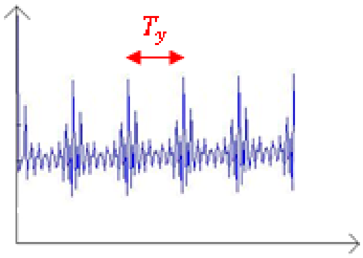
Texture primitive template is calculated after getting the size of texture primitive. In train phase, defect free fabric image is divided into $T_x \times T_y$ blocks, (Zero-padding could be used, if division cause to create smaller blacks). Then, gray mean of each pixel is calculated according to equation $M_{i,j} = \frac{1}{n}\sum_{k=1}^{n} W_{i,j}^{k}$, where $M_{i,j}$ is gray value of each pixel in primitive texture template, $W_{i,j}^{k}$ is gray level value of pixels in the k_th block and n is total number of blocks. (In summary, to calculate gray value of pixel (i,j), it must be compute the mean gray value of all pixels corresponding to $(i,j)^{th}$ index in each block and assigns to $(i,j)^{th}$ pixel in primitive texture template). Through this way, sizes and values of the primitive texture template is resulted.



(a) Fabric image



(b) Horizontal auto-correlation



(c) Vertical auto-correlation

Fig. 1. The periodicity of the fabric texture image

B. Enhancing the Defect Regions

Automatic fabric defect inspection attenuate effects of the background image, steadily that corresponds to defect free regions. On the contrary, there is an strong emphasize on accentuating defected zones, simultaneously. Finally, the defects are detected. Some researchers have done contribution to present some approaches for enhancing the defected images. For example, Sari-Sarraf [3], used information of defects, Abouelela *et al.* [4], applied processing of zero-mean smoothed image to improve defects in image.

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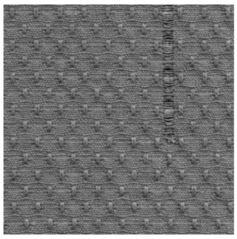
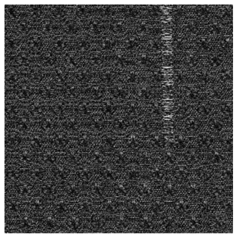
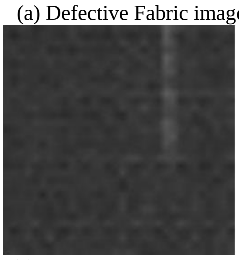


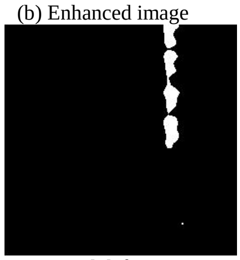
(a) Defective Fabric image



(b) Enhanced image



(c) Mean image



(d) Segmented defect image

Fig. 2. The steps of defects segmentation algorithm

A new approach based upon primitive texture template is introduced to enhance the defect areas in this paper.

Because of the percentage of defects region is smaller than that of the defect free fabric in fabric image, there is a little difference between every texture primitive and texture template calculated according to the above method in non defective regions. But a great difference between them in defect regions is because the noticeable changes arising in their gray and texture structure. The images are subdivided into $T_x \times T_y$ blocks again in the algorithm. The difference between every block and the primitive template is calculated according to the formula $S^k{}_{i,j} = |W^k{}_{i,j} - M_{i,j}|$.

Then all $S^k{}_{i,j}$ are defect normalized according to this formula:

$$S'_{i,j} = \frac{(S^k{}_{i,j} - \mathrm{Min}\left(S^1{}_{i,j}, S^2{}_{i,j}, \ldots, S^n{}_{i,j}\right) * 255)}{\mathrm{Max}\left(S^1{}_{i,j}, S^2{}_{i,j}, \ldots, S^n{}_{i,j}\right) - \mathrm{Min}\left(S^1{}_{i,j}, S^2{}_{i,j}, \ldots, S^n{}_{i,j}\right)} \quad (3)$$

In the formula, Max() and Min() refer to the maximum function and the minimum function respectively. The enhanced image is illustrated in Fig. 2 (b). The method has a better enhancement effect to both intensity defects and geometrical defects than both methods in [3] and [4].

C. Structure of the Mean Image

Because of the existence of high frequency noises, the enhanced image cannot directly segmented into binary image. One method to filtering these noises through structure of the mean image is presented in this paper. at the first step of this method, the enhanced image is partitioned into 8×8 sub-image (Experiments show that this dimension obtains more performance than the others). the mean of each sub-image is calculated via this formula:

$$MV_{i,j} = \frac{1}{64}\sum_{m=0}^{7}\sum_{n=0}^{7} G_{i+m,j+n} \quad (4)$$

in this formula, $MV_{i,j}$ is a pixel that its value is the mean of related sub – image. In the other words, constructed image is smaller than enhanced image (width (length) size is equal to number of windows in horizontal (vertical) side) and the gray level related to (i,j) pixel, is equal to mean of $(i,j)^{th}$ sub-image gray levels that its size is 8×8 in enhanced image (If necessary the zero padding approach is used). Then to stretch this image to the original size using a bilinear interpolation mechanism is used. The high frequency noises can be attenuated effectively by the mean image. It is benefit to the defect segmentation in the next step. The constructed image is shown in Fig. 2 (b).

D. Structure of the Mean Image

In this paper, automatic threshold segmentation according to Otsu's approach is employed to segment the defect image [5]. Otsu's approach is one of the best automatic threshold segmentation methods. The basic idea of this method is to divide pixels of images into two groups by threshold, and then the best threshold is selected through the maximum groups variance between two groups. This method is applied to non defective image in training phase that the segmented image is a quite black image that indicates no defect found in the image.

III. EXPERIMENTS

Image database used in experiments that is provided by Industrial Automation Research Laboratory, Department of Electrical and Electronic Engineering, The University of Hong Kong, approximately 30 images is used that 10 images are non defective for training phase and 20 for testing phase, that is from two types of intensity defects and geometric defects. The primitive template and also the Otsu's approach threshold are extracted in training phase from non defective image, and in testing phase, defective region are distinguished from calculating difference between primitive template and defective image, then the output image is enhanced. The high frequency noises can be attenuated effectively by the mean image and with the extracted threshold from training phase, the defect pattern will be achieved.

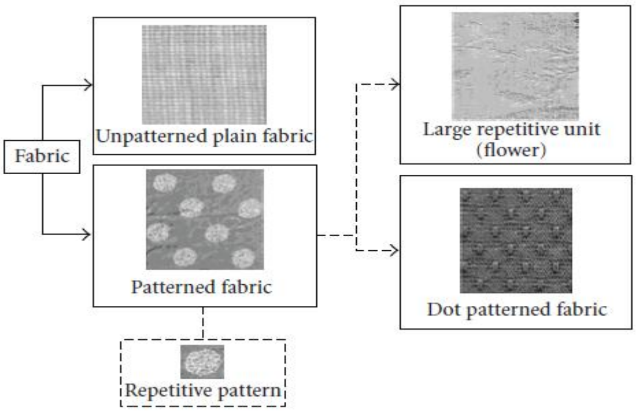
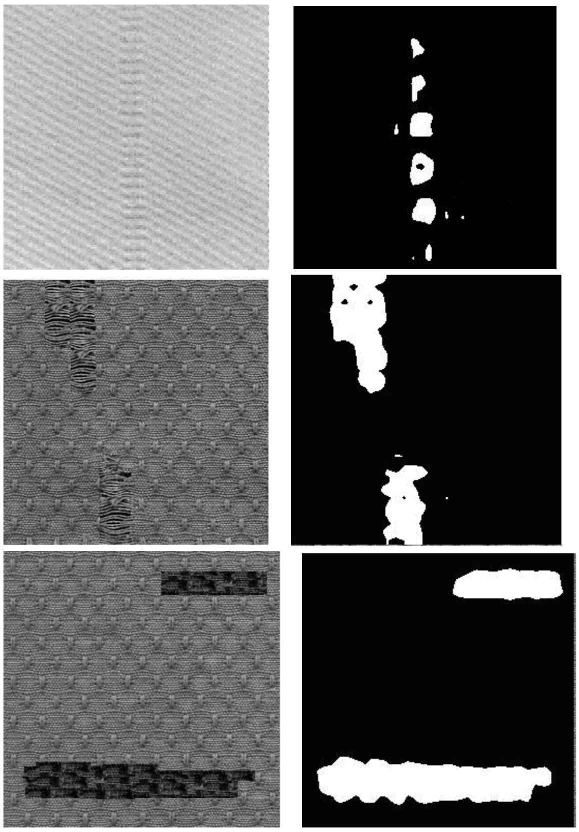
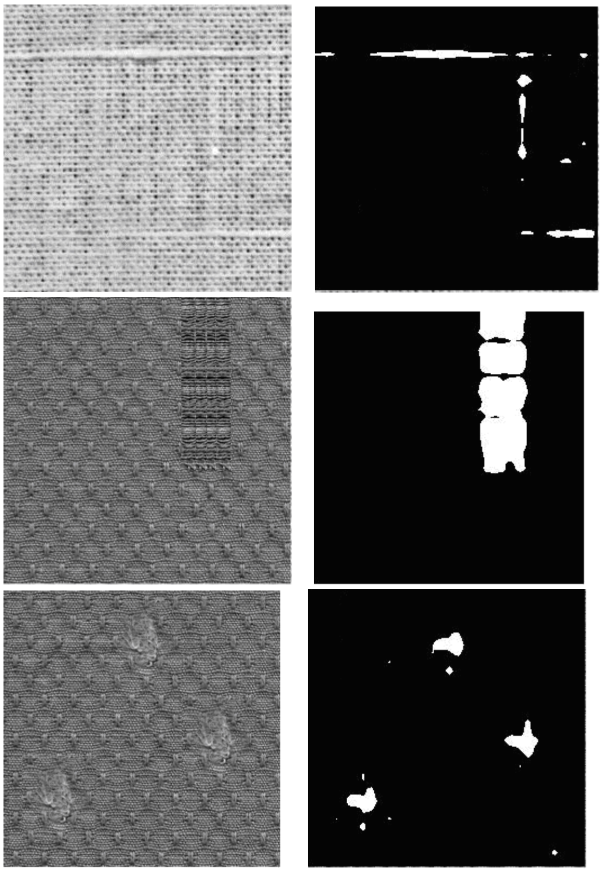


Fig. 3. Classification of fabrics [2]

Some samples of patterned and un-patterned fabrics are shown in Fig.3. In order to prove validity of the proposed approach, some fabric defect images from the Image Base are segmented in the experiments. And the results of segmentation are shown in Fig. 4. In these figures, white regions in defect primitive expressed locations of defective regions. So with this approach, segmentation and localization of defective region are performed effectively. At the end of the algorithm it is benefit to use median filtering to eliminating the noises.



(a) (b)



(a) (b)

Fig. 4. Segmentation result of some patterned and unpatterned defects image, (a) defect image; (b) segmented image

IV. Conclusion

A new fabric defect segmentation approach based on texture primitive is put forward in this paper, in which defect information is accentuated by calculating the difference between texture primitive and primitive template. High frequency information is smoothed by constructing the mean image, and the threshold is automatically selected using Otsu's approach. Also the used algorithm is not based on complicated image processing. So because of its simplicity, and its efficiency, it can be use as a robust algorithm for on-line patterned and un-patterned fabric defect detection.

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References

[1] C. S. Cho , B. M. Chung and M. J. Park. (2005). Development of Real-Time Vision-Based Fabric Inspection System. *IEEE Trans. on Industrial Electronics*. [Online]. Available: http://www.ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=1490697&userType=&tag=1.

[2] F. Tajeripour, E. Kabir and A. Sheikhi. (2008). Fabric Defect Detection Using Modified Local Binary Patterns. *EURASIP Journal on Advances in Signal Processing*. [Online]. Available: http://www.asp.eurasipjournals.com/content/2008/1/783898 .

[3] H. Sari-Sarraf and J. S. Goddard Jr. (1999). Goddard Vision system for on-loom fabric inspection. *IEEE Transactions Industry Application*. [Online]. Available: http://www.ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=00806035

[4] A. Abouelela , H. M. Abbas and H. Eldeeb. (2005). Automated vision system for localizing structural defects in textile fabrics. *Pattern Recognition Letters*. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167865504003794.

[5] N. Otsu., "A threshold selection method from gradation - level histogram," *IEEE Trans. on systems man and cybernetics*, vol. 6, no. 6, pp. 62-66, 1979.

Elham Hoseini received her B.Sc degree in Software Engineering from Shiraz University, Iran in 2009. Currently, she is an Artificial Intelligence Master student in the School of Electrical and Computer Engineering, Shiraz University, Iran. She is a member of the soft computing group since September 2010. Her research interests include digital image processing, data mining, recommender systems and machine learning.

Farnoush Farhadi received her B.Sc degree from Shahid Beheshti University, Iran in 2005 majored in software engineering. She is currently a graduate student of artificial intelligent in School of Electrical and Computer Engineering, Shiraz University, Shiraz, Iran. She is a member of the soft computing group of her school since September 2010. Her research interest is in digital image processing, large-scale data mining for graphs, query answering, task assignment and social networks.

Farshad Tajeripour received the B.Sc. and M.Sc. degrees in electrical engineering from Shiraz University, in 1994 and 1997, respectively, and the Ph.D. degree in electrical engineering from the Tarbiat Modarres University of Tehran, in 2007. In 2007, he joined the Department of Electrical and Computer Engineering at Shiraz University, Shiraz, as an Assistant Professor. His research interests include digital image processing, machine vision, medical image processing, signal processing, and the design and implementation of vision based inspection systems. He has published several papers in the fields of pattern recognition, signal and image processing.