

July 2012

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Recommended Citation

Asha, V.; Nagabhushan, P.; and Bhajantri, N. U. (2012) "Similarity Measures for Automatic Defect Detection on Patterned Textures," *International Journal of Image Processing and Vision Science*: Vol. 1 : Iss. 1 , Article 5.

DOI: 10.47893/IJIPVS.2012.1004

Available at: <https://www.interscience.in/ijipvs/vol1/iss1/5>

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Similarity Measures for Automatic Defect Detection on Patterned Textures

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Abstract — Similarity measures are widely used in various applications such as information retrieval, image and object recognition, text retrieval, and web data search. In this paper, we propose similarity-based methods for defect detection on patterned textures using five different similarity measures, viz., *Normalized Histogram Intersection Coefficient*, *Bhattacharyya Coefficient*, *Pearson Product-moment Correlation Coefficient*, *Jaccard Coefficient* and *Cosine-angle Coefficient*. Periodic blocks are extracted from each input defective image and similarity matrix is obtained based on the similarity coefficient of histogram of each periodic block with respect to itself and other all periodic blocks. Each similarity matrix is transformed into dissimilarity matrix containing true-distance metrics and Ward's hierarchical clustering is performed to discern between defective and defect-free blocks. Performance of the proposed method is evaluated for each similarity measure based on precision, recall and accuracy for various real fabric images with defects such as broken end, hole, thin bar, thick bar, netting multiple, knot, and missing pick.

Keywords - Cluster, Defect, Histogram, Periodicity, Similarity measure.

I. INTRODUCTION

Patterned textures are found everywhere in our day-to-day life in many applications such as textile fabrics, wallpapers, and ceramics. Product inspection is key issue in the quality control of various products in industries. Conventional human-vision based inspections involve high labor cost and skilled inspectors. Moreover, in the conventional human-vision based inspections, lack of repeatability and reproducibility of inspection results due to fatigue and subjective nature of human inspections and imperfect defect detection are always common. These, in turn, affect the quality of inspection and the production rate. An automated inspection system can help in reducing the inspection time and increasing the production rate. Among various industries, textile industry is one of the biggest

traditional industries requiring automated inspection. Due to complexity in the design, existence of numerous categories of patterns, and similarity between the defect and background, most of the methods in literature depend on training stage with numerous defect-free samples for obtaining decision-boundaries or thresholds prior to defect detection [1-6]. In this paper, we propose a method of defect detection on patterned fabric images without any training stage with the help of texture-periodicity and clustering technique based on several similarity measures. The main contributions of this research can be summarized as follows:

- The proposed method of defect detection can be used for any type of patterned texture.
- The proposed method does not require any training stage with defect-free samples for decision boundaries or thresholds unlike other methods. As a result, the proposed method does not need huge memory space for storage of defect-free samples.
- Detection of defective and defect-free periodic units is automatically carried out based on cluster analysis without human intervention.

The program for the proposed algorithm is written in Matlab-7.0 and run in a Pentium-IV Personal Computer of RAM capacity 2 GB. The organization of this paper is as follows: Section-II presents a brief review on several similarity measures. Section-III presents the proposed method of defect detection, experiments on several patterned textures of real fabric images with defects, and evaluation of the performance parameters of the proposed algorithm for various similarity measures. Section-III has the conclusions.

II. SIMILARITY MEASURES

Similarity measures are widely used in numerous applications including information retrieval, image and object recognition, text retrieval and web data search (eg., [8-13]). The similarity measure reflects the degree of closeness of the target objects and can be used to distinguish the

clusters embedded in the data of our interest based on some characteristics. In many cases, these characteristics are dependent on the test data, and hence there is strictly no measure that can be considered universally the best for all kinds of clustering problems. In this paper, we intend to use different similarity measures, viz., normalized histogram intersection coefficient, Bhattacharyya coefficient, Pearson product-moment correlation coefficient, Jaccard coefficient, and cosine-angle coefficient (abbreviated as *Hist_norm*, *Bhat*, *Pear*, *Jac* and *Cos* respectively) for the defect detection method and study the performance for detecting various defects. These similarity measures are briefly discussed as follows:

A. Normalized Histogram Intersection Coefficient

Histogram intersection coefficient counts the common number of pixels of same gray value between two histograms [14]. If p and q are the probability distributions of two images A and B with gray values $i = 1, 2, \dots, N$ as common random variables, then the histogram intersection coefficient is given by

$$S_{Hist}(A, B) = \sum_{i=1}^N \min(p(i), q(i)) \quad (1)$$

Upon normalizing the coefficient over all gray values, the range becomes (0, 1) indicating that the normalized histogram intersection coefficient (S_{Hist_norm}) is 1 if the gray values of the two images exactly match and is 0 if not.

B. Bhattacharyya Coefficient

The Bhattacharyya coefficient is a divergence-type measure between two distributions [15]. If p and q are the probability distributions of two images A and B with gray values $i = 1, 2, \dots, N$ as common random variables, the Bhattacharyya coefficient is given by

$$S_{Bhat}(A, B) = \sum_{i=1}^N \sqrt{p(i)q(i)} \quad (2)$$

The Bhattacharyya measure has a simple geometric interpretation as the cosine of the angle between the two N -dimensional vectors $(\sqrt{p(1)}, \dots, \sqrt{p(N)})^T$ and $(\sqrt{q(1)}, \dots, \sqrt{q(N)})^T$. Thus, if the two distributions are identical, we have the following condition:

$$\sum_{i=1}^N \sqrt{p(i)q(i)} = \sum_{i=1}^N \sqrt{p(i)p(i)} = \sum_{i=1}^N \sqrt{q(i)q(i)} = 1$$

If the two distributions do not match at all, the measure is 0. Thus, the Bhattacharyya measure ranges between 0 and 1.

C. Pearson Product-moment Correlation Coefficient

Pearson's product-moment correlation coefficient is another measure of the extent to which signals $\mathbf{x} = \{x_i | i = 1, 2, \dots, N\}$ and $\mathbf{y} = \{y_i | i = 1, 2, \dots, N\}$ are related and is given by [16]

$$S_{Pear}(x, y) = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (y_i - \bar{y})^2}} \quad (3)$$

$$\text{where, } \bar{x} = \frac{1}{N} \sum_{i=1}^N x_i \text{ and } \bar{y} = \frac{1}{N} \sum_{i=1}^N y_i$$

It ranges from +1 to -1. The coefficient is 1 when both \mathbf{x} and \mathbf{y} have positive correlation between them and is -1 when \mathbf{x} and \mathbf{y} have negative correlation. When there is no correlation between \mathbf{x} and \mathbf{y} , the coefficient takes the value zero.

D. Jaccard Coefficient

The Jaccard coefficient measures similarity as the intersection divided by the union of the objects [17]. If two objects are represented in vector form as \vec{t}_a and \vec{t}_b , the Jaccard coefficient compares the sum weight of shared terms to the sum weight of terms that are present in either of the two objects but are not the shared terms. The Jaccard coefficient is given by

$$S_{Jac}(\vec{t}_a, \vec{t}_b) = \frac{\vec{t}_a \cdot \vec{t}_b}{|\vec{t}_a|^2 + |\vec{t}_b|^2 - |\vec{t}_a \cap \vec{t}_b|} \quad (4)$$

The Jaccard coefficient ranges between 0 and 1. It is 1 when two objects are identical and 0 when the objects are completely different.

E. Cosine-angle Coefficient

If two objects are represented as vectors, the similarity of two objects corresponds to the correlation between the vectors [18]. This is specified in terms of the cosine of the angle between the two vectors and is called cosine-angle coefficient. Cosine-angle coefficient is one of the most popular similarity measures applied to text documents, such as in numerous information retrieval applications [21]. The cosine-angle coefficient between two objects represented by vectors \vec{t}_a and \vec{t}_b is given by

$$S_{Cos}(\vec{t}_a, \vec{t}_b) = \frac{\vec{t}_a \cdot \vec{t}_b}{|\vec{t}_a| |\vec{t}_b|} \quad (5)$$

where \vec{t}_a and \vec{t}_b are N -dimensional vectors over the term set $T = \{t_1, t_2, \dots, t_N\}$. Each dimension represents a term with its weight in the document, which is non-negative. As a result, the cosine-angle measure is non-negative and is bounded between 0 and 1. When two documents are identical, the cosine similarity is exactly one.

III. PROPOSED METHOD OF DEFECT DETECTION

A. Algorithm Description

When two objects under inspection tend to become similar, the similarity coefficient tends to be 1. Motivated by this fact, the algorithm for defect detection is proposed based on similarity measures of histograms of the periodic blocks

of the image under inspection. There are three main assumptions in the proposed algorithm as follows:

- Test image is of at least two periodic units in horizontal direction and two in vertical direction whose dimensions are known apriori.
- Number of defective periodic units is always less than the number of defect-free periodic units.
- Test images are from imaging system oriented perpendicular to the surface of the product such as textile fabric.

An image under inspection may have fractional periodic blocks also. Hence, based on our earlier approach of analyzing patterned textures [19], four cropped images containing complete number of periodic blocks are obtained from the defective test image by cropping it from all four corners (top-left, bottom-left, top-right and bottom-right). If g is the an image of size $M \times N$ with row periodicity P_r (i.e., number of columns in a periodic unit) and column periodicity P_c (i.e., number of rows in a periodic unit), then the size of cropped image g_{crop} is $M_{crop} \times N_{crop}$ where M_{crop} and N_{crop} are measured from top-left, bottom-left, top-right and bottom-right corners and are given by the following equations:

$$M_{crop} = \text{floor}(M / P_c) \times P_c \quad (6)$$

$$N_{crop} = \text{floor}(N / P_r) \times P_r \quad (7)$$

Each cropped image is split into several periodic blocks of size $P_c \times P_r$. Similarity measures based on first-order histograms are calculated for each periodic block with respect to itself and all other periodic blocks to get a similarity matrix. In order to convert the similarity matrix S to dissimilarity matrix D containing distance metrics, we apply *Similarity-dissimilarity Transformation* such that the dissimilarity matrix satisfies the conditions of true-metrics (viz., non-negativity, self-distance, symmetry and triangular-inequality) as below:

$$\begin{aligned} D_{ij} &\geq 0 \\ D_{ij} &= 0, \text{ if } i = j \\ D_{ij} &= D_{ji} \\ D_{ij} &\leq D_{ik} + D_{kj}, i \neq j \neq k \end{aligned} \quad (8)$$

The transformation equations which we apply for converting similarity matrix into dissimilarity matrix for all similarity measures are shown in Table 1.

For an image with n number of periodic blocks, the dissimilarity matrix containing the distance metrics is of size $n \times n$ as below:

$$D_{\text{method}} = \begin{bmatrix} D_{1,1} & D_{1,2} & \cdots & D_{1,n-1} & D_{1,n} \\ D_{2,1} & D_{2,2} & \cdots & D_{2,n-1} & D_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ D_{n-1,1} & D_{n-1,2} & \cdots & D_{n-1,n-1} & D_{n-1,n} \\ D_{n,1} & D_{n,2} & \cdots & D_{n,n-1} & D_{n,n} \end{bmatrix} \quad (9)$$

where, method \in (*Hist, Bhat, Pear, Jac, Cos*)

Since dissimilarity of a periodic block with itself is zero and dissimilarity between i^{th} periodic block and j^{th} periodic block is same as that between j^{th} periodic block and i^{th} periodic block, the dissimilarity matrix becomes a diagonally symmetric matrix hollow matrix as below:

$$D_{\text{method}} = \begin{bmatrix} D_{1,1} & & & & \\ D_{2,1} & D_{2,2} & & & \\ \vdots & \vdots & \ddots & & \\ D_{n-1,1} & D_{n-1,2} & \cdots & D_{n-1,n-1} & \\ D_{n,1} & D_{n,2} & \cdots & D_{n,n-1} & D_{n,n} \end{bmatrix} \quad (10)$$

where, method \in (*Hist, Bhat, Pear, Jac, Cos*)

It may be noted that because the matrix is symmetric about the diagonal, the upper diagonal elements are not filled for the sake of simplicity. This dissimilarity matrix is directly given as input to the Ward's hierarchical clustering [20] to automatically get defective and defect-free periodic blocks from each cropped image.

TABLE I. TRANSFORMATION EQUATION FOR CONVERTING SIMILARITY MEASURES TO DISTANCE METRIC AND THE RANGES BEFORE AND AFTER TRANSFORMATION (NOTE: THE VALUE 1 IN SIMILARITY MEASURES INDICATE PERFECT MATCHING BETWEEN TWO OBJECTS, WHEREAS THE VALUE 0 IN DISSIMILARITY MEASURES INDICATE PERFECT MATCHING BETWEEN TWO OBJECTS).

Similarity measure	Range for similarity measure	Transformation equation to get dissimilarity measure (distance metric)	Range for dissimilarity measure
Normalized histogram intersection coefficient (S_{Hist_norm})	[0, 1]	$D_{Hist_norm} = \sqrt{1 - S_{Hist_norm}}$	[0, 1]
Bhattacharyya coefficient (S_{Bhat})	[0, 1]	$D_{Bhat} = \sqrt{1 - S_{Bhat}}$	[0, 1]
Pearson product-moment correlation coefficient (S_{Pear})	[-1, 1]	$D_{Pear} = \sqrt{0.5 \times (1 - S_{Pear})}$	[0, 1]
Jaccard coefficient (S_{Jac})	[0, 1]	$D_{Jac} = \sqrt{1 - S_{Jac}}$	[0, 1]
Cosine-angle coefficient (S_{Cos})	[0, 1]	$D_{Cos} = \sqrt{1 - S_{Cos}}$	[0, 1]

B. Experiments on Defective Fabric Images

In order to test the proposed algorithm for defect detection, defective dot-patterned fabric images with defects – broken end, hole, thin bar, thick bar, netting multiple, knot and missing pick are considered as shown in Fig. 1. Following (6) and (7), four cropped images containing complete number of periodic blocks are obtained from each test image with the help of periodicities known apriori. Each cropped image is split into several periodic blocks and dissimilarity matrices containing distance metrics are

obtained through transformation equations given in Table 1. Each dissimilarity matrix is subjected to Ward’s hierarchical clustering and defective periodic blocks are automatically identified.

C. Performance Evaluation of the Proposed Algorithm

In order to access the performance of the proposed method, performance parameters, viz., precision, recall and accuracy [21] are all evaluated in terms of true positive (TP), true negative (TN), false positive (FP), and false negative (FN), where true positive refers to the number of defective periodic blocks identified as defective, true negative is defined as the number of defect-free periodic blocks identified as defect-free, false positive refers to the number of defect-free periodic blocks identified as defective and false negative refers to the number of defective periodic blocks identified as defect-free.

TABLE II. SUMMARY OF PERFORMANCE PARAMETERS AVERAGED OVER ALL CROPPED IMAGES FOR EACH DEFECTIVE IMAGE (NOTE: BE=BROKEN END, HE=HOLE, TNB=THIN BAR, TKB=THICK BAR, NM=NETTING MULTIPLE, KN=KNOT, AND MP=MISSING PICK)

Similarity measure	Defect	No. of periodic blocks	Precision (%)	Recall (%)	Accuracy (%)
Normalized histogram intersection coefficient	BE	252	100	80.0	96.8
	HE	252	100	71.9	92.9
	TNB	252	100	75.0	98.4
	TKB	252	100	91.7	97.6
	NM	252	88.2	82.9	94.8
	KN	252	100	59.8	89.3
	MP	252	100	70.3	92.9
Bhattacharyya coefficient	BE	252	100	80.0	96.8
	HE	252	100	71.9	92.9
	TNB	252	100	87.5	99.2
	TKB	252	100	91.7	97.6
	NM	252	82.5	78.6	93.3
	KN	252	100	56.9	88.5
	MP	252	100	70.3	92.9
Pearson product-moment correlation coefficient	BE	252	100	80.0	96.8
	HE	252	100	71.9	92.9
	TNB	252	100	58.3	96.8
	TKB	252	100	66.5	90.9
	NM	252	82.5	70.8	92.5
	KN	252	100	64.3	90.5
	MP	252	90	57.8	89.3
Jaccard coefficient	BE	252	100	80.0	96.8
	HE	252	100	71.9	92.9
	TNB	252	100	58.3	96.8
	TKB	252	100	88.5	96.8
	NM	252	89.2	76.1	95.2
	KN	252	100	73.6	92.9
	MP	252	90	59.4	89.3
Cosine-angle coefficient	BE	252	100	80.0	96.8
	TNB	252	100	71.9	92.9
	TKB	252	100	66.5	90.9
	NM	252	92.3	71.1	95.2
	KN	252	100	73.1	92.9
	MP	252	92	59.4	89.7

Recall is the number of true positives divided by the sum of true positives and false negatives that are periodic blocks not labeled as belonging to the positive class but should have been and is calculated as $TP/(TP+FN)$. Precision is the number of periodic blocks correctly labeled as belonging to the positive class divided by the total number of periodic blocks labeled as belonging to the positive class and is calculated as $TP/(TP+FP)$. Recall is the number of true positives divided by the sum of true positives and false negatives that are periodic blocks not labeled as belonging to the positive class but should have been and is calculated as $TP/(TP+FN)$. Accuracy is the measure of success rate that considers detection rates of defective and defect-free periodic blocks and is calculated as $(TP+TN)/(TP+TN+FP+FN)$. Though the number of periodic blocks from a defective input image is same for all of its cropped images, the number of defective periodic blocks identified does not have to be same for all cropped images. This is mainly due to the fact that the contribution of defect in each periodic block may differ for different cropped images. The performance parameters averaged over all cropped images for each defective image are given in Table 2 for each defective image. These performance parameters are averaged for all defective images and given in Table 3 for each similarity measure based on a total number of 1764 periodic blocks. The precision rates are more than 96% and the accuracies are more than 92% without any training stage for all similarity measures. Hence, a defect detection system can be built with any of these measures. The method based on cosine-angle coefficient has the least recall rate. Normalized histogram intersection coefficient, Bhattacharyya coefficient and Jaccard coefficient yield almost same accuracy with a recall rate better than 72%. Relatively less recall rates indicate that there are few false negatives identified by the proposed method. However, because our approach based on similarity coefficients yields high precision and accuracy, it can contribute to automatic defect detection in fabric industries.

TABLE III. SUMMARY OF PERFORMANCE PARAMETERS AVERAGED OVER ALL DEFECTIVE IMAGES FOR EACH METHOD

Similarity measure	Precision (%)	Recall (%)	Accuracy (%)
Normalized histogram intersection coefficient	98.3	75.9	94.7
Bhattacharyya coefficient	97.5	76.7	94.4
Pearson product-moment correlation coefficient	96.1	67.1	92.8
Jaccard coefficient	97.0	72.5	94.4
Cosine-angle coefficient	97.7	68.6	93.6

D. Concept of Defect Fusion

Though the number of periodic blocks from a defective input image is same for all of its cropped images, defects identified from each cropped image do not give an overview of total defects though the number of periodic blocks is same for each cropped image. Hence, we use the concept of

defect fusion proposed in [19] that involves merging of boundaries of defective blocks, morphological filling [22] and Canny edge detection [22] to get the overview of defects. In order to illustrate this, let us consider the defective image with defect – hole (Fig. 1(b)). The defective blocks identified from each cropped image of the defective fabric (based on normalized histogram intersection coefficient) are shown in Fig. 2, where the boundaries of the defective blocks are highlighted using white pixels. The boundaries of defective periodic blocks identified from each cropped image are shown in Fig. 3 (a) by superimposing on the original defective image and in Fig. 3 (b) separately on plain background. The morphologically filled zones are shown in Fig. 3 (c) and the edges extracted using Canny's edge operator are shown superimposed on original defective image in Fig. 3 (d). Thus, it is clear that *fusion* of defects from all 4 cropped images helps in getting an overview of total defects in the input image. Following the concept of defect fusion, final results after merging of defects, morphological filling and edge detection for all defective images are shown in Fig. 4 for different similarity measures.

IV. CONCLUSIONS

Through experiments on real fabric images with different defects, we have shown that similarity based measures can be effectively used for automatic defect detection on patterned textures. We also suggest that similarity based matrices can be transformed into dissimilarity based matrices containing true distance metrics through transformation equations and can be effectively utilized for hierarchical clustering. Effectiveness of the proposed method for defect detection is demonstrated through experiments on real fabric images with various defects.

ACKNOWLEDGMENT

The authors would like to thank Dr. Henry Y. T. Ngan, Research Associate of Industrial Automation Research Laboratory, Department of Electrical and Electronic Engineering, The University of Hong Kong, for providing the database of patterned fabrics.

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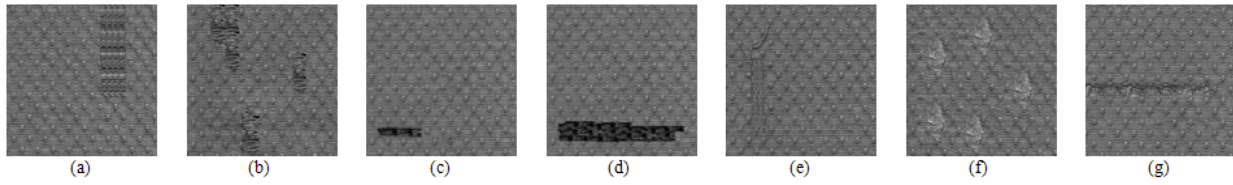


Figure 1. Real fabric images with defect - (a) broken end; (b) hole; (c) thin bar; (d) thick bar; (e) netting multiple; (f) knot; (g) missing pick.

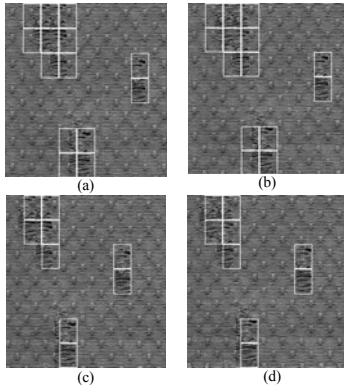


Figure 2. Sample result of defect detection on each cropped image for the test image with defect – hole based on normalized histogram intersection coefficient. Defective periodic blocks identified from (a) top-left (b) bottom-left (c) top-right and (d) bottom-right corners of the test image with their boundaries highlighted using white pixels.

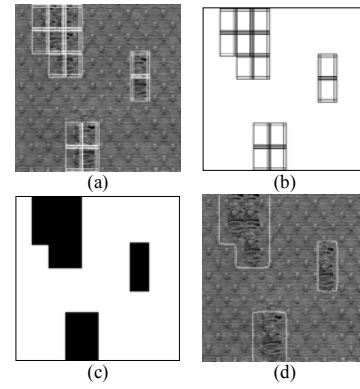


Figure 3. Illustration of defect fusion: (a) Boundaries of the defective blocks identified from each cropped image shown superimposed on the original image; (b) Boundaries of the defective blocks shown separately on plain background; (c) Result of morphological filling; (d) Canny edge identified shown superimposed on original defective image using white pixels.

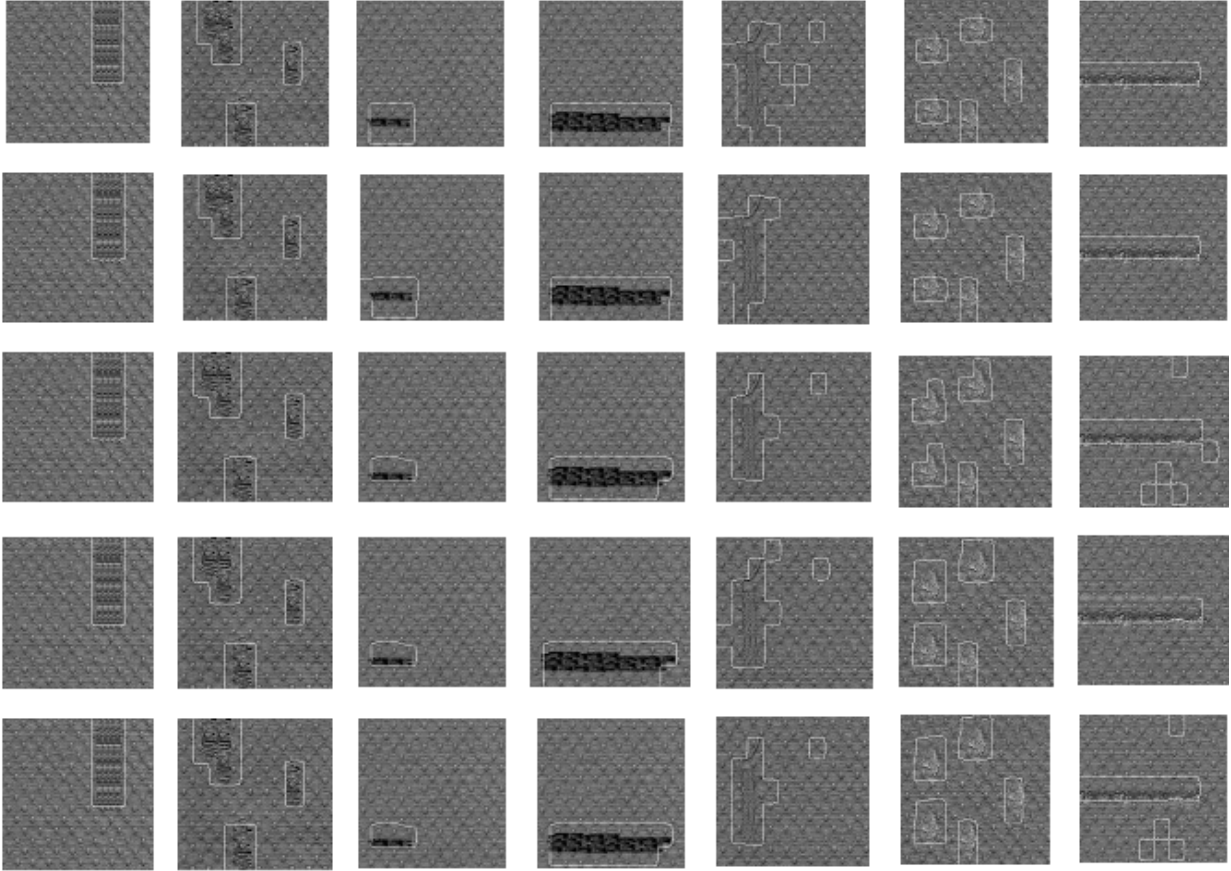


Figure 4. Final result of defect detection on defective fabric images: First, second, third, fourth and fifth rows show the final result of defect detection after merging of defects, morphological filling and edge detection based on normalized histogram coefficient, Bhattacharyya coefficient, Pearson product-moment correlation coefficient, Jaccard coefficient and Cosine-angle coefficient respectively; First, second, third, fourth, fifth, sixth and seventh columns show the real fabric images with defects – broken end, hole, thin bar, thick bar, netting multiple, knot, and missing pick respectively.