Defect detection in textile fabrics with snake active contour and support vector machines

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Abstract. This paper presents the automatic fabric defect detection in the textile manufacturing industry. The method utilizes edge detection via Snake active contour models to extract the fabric feature. The two-dimensional principal component analysis is employed for data reduction. Then, the outcome of the data reduction passes through the support vector machine as the classifier for classification. The performance of the method is evaluated with the 900 – fabric images for efficiency and effectiveness. The experimental results show that the method is able to detect the defection on the textile with the average accuracy of 98.77%. The results indicate that the proposed method is outstanding on the defect detection of the textile.

1. Introduction
Nowadays, the textile manufacturing industry employs the machines to handle the job for the large volume and rapidity. Eventually, the defection on the fabric could occur due to the error of the machine. The inspection must be performed instantly to detect the defection to prevent further damage on the production line. The defect detection to spot the defect fabric is necessary on quality control of the process. In the past, the defect detection utilized simple process via visual inspection. The overall accuracy yielded no more than 80% [1]. Thus, many researches and developments have continuously been explored on the new techniques and different methods issue for the high effectiveness and more accurate. Out of these various passes, the principle of image processing techniques [2], [3] give promising result of the effectiveness and accuracy on the detection since the computer, instead of the human being, is employed to make the decision on the defect.

2. Literature review
The fabric defect detection approaches can largely be classified into 4 groups; i.e. statistical, spectral, model based, and structural approaches. Some of the previous works on statistical approach utilized Fisher criterion based denoising auto encoding [4]. The obtained results have high detection accuracy even with insufficient negative samples but time consume. Some utilized Genetic algorithm with homogeneity, contrast, correlation, hue, and saturation to measure the performance [5]. The method needed very large number of high quality images. The Kernal principal component analysis [6] was also employed. The measurements were on the detection success rate, specificity, and sensitivity. The method high true detection rate and low cost for online fabric inspection. Also artificial neural back propagation technique was introduced with 5 features as the feature input [7]. The efficiency of the model was reliable to identify the defect but not appropriate for all types of defects. Another worked with the pulse coupled neural network with mean and standard deviation to measure the performance [8], utilizing embedded system for less computation.
Some on spectral approach utilized 2D Fast Fourier transform with several measurements [9]. The method determined yarn paths even in critical circumstance. The Raden signature and Discrete wavelet transform [10] was introduced with variance, uniformity, and entropy to measure. The method applied to pattern less fabrics and patterned fabrics. Some utilized the discrete cosine transform [11] which would be extended for colour image. On the model based approach, some applied Fuzzy clustering [12] with blind weave detection which need no prior knowledge of the fabric. Also, Neuro Fuzzy classifier was employed with spatial and spectral features [13] but the method needed large data samples to improve the accuracy. Some introduced multi resolution combined statistical and spatial frequency with various measurements [14]. The method yielded good success rate of classification. On the structural approach, some utilized canny edge detection [15] which have fast detection and extraction on the process. The other employed discrete wavelet transform [16]. The method was able to label the boundaries of the defective areas.

This paper interests on structural approach utilizing snake active contour models for defect detection of the textile with the two-dimensional principal component analysis for the data reduction as the tools for feature extraction and the support vector machine as the classifier for classification. The objectives are on analysing the local fabric textile in physical dimension or in general of the textile, to increase the accuracy with efficiency and effectiveness on the defect detection of the textile, to increase the effective productive in the line of product, increase quality of the outputs, reduce time consumption in justification on the outputs and reduce cost of operation via advance technology.

This paper is organized into five sections, including this introduction and literature review sections. Section 3 presents all processed of defect detection method and data. The experimental results are shown in section 4. Finally, the conclusion of this paper are given in section 5.

3. Data and method

3.1. Data
The data in this work consisted of 5 defection groups of the textile materials, each with 50 figures, total of 250 images. Each image has the 256*256 pixels on the gray scale. Each group are as follows: Group A – Gout, Group B – Knot, Group C – Burl, Group D - Warp float, and Group E - Big knot. Figure 1 shows the defection on each group.

![Figure 1. The defection of the fabric a. gout, b. knot, c. burl, d. warp float, and e. big knot.](image)

3.2. Method
The proposed method is shown in figure 2 and the processes are separated into 2 groups; i.e. feature preparation and classification. The first group contained 2 units; i.e. feature extraction and data reduction. First, the feature of the image is extracted via the Snake Active Contour Models. Then, the
data reduction is follow, utilizing 2DPCA to reduce size of the image for training and testing, characteristic of the image still preserved on the process. Finally, the SVM is employed as the classifier for classification.

![Figure 2. The proposed method.](image)

The proposed method is as follow:

1) Inspected image
   The inspected image is the image of 256*256 pixels on gray scale level as the input to the system for feature extraction.

2) Feature Preparation
   Feature preparation on the top box in figure 2 consists of 2 units; i.e. feature extraction with Snake active contour model and data reduction with 2DPCA.
   a) Snake active contour model [17]: A snake falls into closest local energy minimum. The local minimum of the snake energy comprise the set of alternative solutions. A higher level knowledge is needed to choose the correct one from these solution, High-level reasoning and user interaction. These high-level methods can interact with the contour model by pushing it toward an appropriate local minimum. They rely on other mechanisms to place them near the desired contour. The existence of such an initializer is application dependent. Even in the case of manual initialization, snakes are quite powerful in refining the user’s input. Parametric representation: $v(s) = (x(s), y(s))$. Snake Energy is representation in eq.1

   \[ E_{\text{snake}} = \int E_{\text{int}}(v(s)) + E_{\text{image}}(v(s)) + E_{\text{con}}(v(s)) ds \]  \hspace{1cm} (1)

   Where $E_{\text{int}}$ = internal energy due to bending; $E_{\text{image}}$ = image forces pushing the snake toward image features; $E_{\text{con}}$ = external constants are responsible for putting the snake near the desired local minimum. The snake is a controlled continuity spline.

   b) 2DPCA is only to eliminate the relevance of the image column and ignore the relevance of image in row [18]. The first one is in horizontal direction and the second is in vertical direction. The process of 2DPCA is described as follow: given image A, the feature matrix B is obtain by the compression of 2D image in horizontal direction in eq.2

   \[ B = AU \]  \hspace{1cm} (2)

   Then, transpose B and input BT into 2DPCA, and determine the transform matrix V. Project BT onto V in eq.3.
CT=BTV \tag{3}

The result Feature matrix is shown in eq.4

C=VTB \tag{4}

3) Classification

If features are extracted well, then any simple classifier is appropriate. SVM is a supervised machine learning paradigm capable of solving linear and non-linear classification and regression problems. SVM generates input-output mapping functions from a set of labeled training data. The goal of SVM is to produce a model (based on the training data) which classifies the test data. A classification task usually involves separating data into training and testing sets. SVM can classify data separated by non-linear and linear boundaries. SVM maps input vectors to a higher dimensional space where a maximal separating hyperplane is constructed. Two parallel hyperplanes are constructed on each side of the hyperplane that maximizes the distance between the two parallel hyperplanes. An assumption is made that the larger the margin or distance between these parallel hyperplanes the better the generalization error of the classifier [19].

![Figure 3. Group of the defect image SVM classification.](image)

4. Experiments and experimental results

We classified images into two categories: defect and non-defect. We used 50 data to train and another 100 data to test each dataset. Additionally, we employed a three-fold cross-validation criterion to train and test. The performance of the classifier was evaluated based on the calculation of the following accuracy.

| Image Prototype | Classification detection by SVM | % Accuracy |
|------------------|----------------------------------|------------|
|                  | Defect | Non-defect |                  |
| Non-defect       | 0      | 150        | 100              |
| Gout             | 148    | 2          | 98.67            |
| Knot             | 147    | 3          | 98.00            |
| Burl             | 148    | 2          | 98.67            |
| Warp float       | 147    | 3          | 98.00            |
| Big knot         | 149    | 1          | 99.33            |
| Average          |        |            | 98.77            |
Table 1 shows the detect defection efficiency of the textile. Utilizing the combination of structural approach with Snake active contour model for feature extraction and 2DPCA for data reduction as the feature preparation and support vector machine as the classifier for classification, the average accuracy on the classification of 98.77% is achieved. Example of defect and non-defect images shown in figure 4.

**Figure 4.** Example of defect and non-defect images.

5. **Conclusion**

The experimental result indicates that the proposed method, which composed of the combined process of the edge detection with snake active contour model and 2DPCA for feature preparation and support vector machine as the classifier for classification, yields an outstanding average accuracy on justification the defect textile with the appropriate data size on the output from 2DPCA. This process preserved characteristic of the materials and had less time consuming on the training and testing. However, the amount of illumination still create some problem. In this experiment, the limitation are as follows; the appropriate light condition is on day time only and also need appropriate distance on focusing the textile. However, the method is able to apply in other areas but need the amount of data large enough for training and testing on each group.
References

[1] R. Chin, “Automated visual inspection techniques and applications: A bibliography,” Pattern Recognition 15(4), pp.343-357,1982.

[2] M. Fathu Nisha, P. Vasuki, and S. Mohamed Monsoor Roomi, “Survey on various defect detection and classification methods in fabric images”, J. Environ. Nanotechnol., Vol.6 No.2, pp.20-29, 2017.

[3] B. Mingde, S. Zhigang and L. Yesong, “Textural fabric defect detection using adaptive quantized gray-level co-cocorrence matrix and support vector description data,” Information Technology Journal, Vol.11, No.6, pp.673-685, 2012.

[4] Yundong Li, Weigang Zhao and Jiahao Pan, “Deformable patterned fabric defect detection with fisher criterion based deep learning”, IEEE Trans. on Automation Sci. Engg., pp. 01-09, 2016.

[5] P. Dakhole, S. Kalode and A. Patel, “Fabric fault detection using image processing matlab,” Int. J. Emerging Trends Engg. Management Res., 2(1), 2016.

[6] Junfeng Jing, Xiaoting Fan and Penegfei Li, “Automated fabric defect detection based on multiple gabor filters and KPCA”, Int. J. of Multimedia and Ubiquitous Eng., 11(6), pp.93-106,2016. doi:10.14257/ijmune.2016.11.6.09

[7] Gagandeep Singh, Gurpadam Singh and Mandep Kaur, Fabric Defect Detection using series of image Processing Algorithm & ANN operation, Global J., Comp. Tech., 4(2), pp. 225-228, 2016.

[8] Tiangpeng Feng, Lian Zou, Jia Yan, Wenxuan Shi, Yifeng Liu, Cien Fan and Dexiang Deng, Real time fabric defect detection using accelerated small scale over completed dictionary of sparse coding, Int. J. Advanced Robotic Systems., 13(1), 01-09(2016). doi: 10.5772/62058

[9] Nasira and Banumathi, P. M., Plain woven fabric defect detection based on image processing and artificial neural networks, Int. J. Comp. Trends Tech., 6(4), 226-229(2013).

[10] Dandan Zhu, Ruru Pan and Wiedong Gao, Yarn dyed fabric defect detection based on autocorrelation function and GLCM, AUTEX Research J., 15(3), 226-232(2015). doi:10.1515/aut-2015-0001

[11] Ali Rebhi, Sabeur Abid and Farhat Fraeich, Texture defect detection using local homogeneity and discrete cosine transform, World Applied sciences Journal, 31(9), 1677-1683(2014). doi:10.5829/idosi.wasj.2014.31.09.156

[12] Schneider, and Dorit Merhof, D., Blind Weave Detection for Woven fabrics, Springer, Dorian Pattern Anal. Appl., 725-737 (2014).

[13] Eldessouki, M., Hassan, M., Qushqari, K. and Shady, E., Application of principal component analysis to boost the performance of an automated fabric fault detector and classifier, Fibers and Textiles in Eastern Europe, 51-57(2014).

[14] Sabeenian, R. S., Paramasivam, M. E. and Dinesh, P. M., Computer vision based defect detection and identification in handloom silk fabrics, Int. J. of Comp. Appl., 42(17), 41-48(2012).

[15] Halimi Abdellah, Roukhe Ahmed and Ouhmad Slimane, Defect detection and identification in textile fabric by SVM Method, IOSR J. Eng., 4(12), 69-77(2014).

[16] Ibrahim Celik, Cannan Dulger and Mehmet Topalbekiroglu, L., Fabric defect detection using linear filtering and morphological operations, Indian J. Fibre and Textile Research, 39(3), 254-259(2014).

[17] M. Klass, A. Witkin, and D. Terzopoulos, “Snake: Active countour models,” International Journal of Computer Vision, pp. 321-331,1988.

[18] A. Srikaew, K. Attakikimoncol and W. Kidsang, “Detection of Defect in Textile Fabrics using Optimal Gabor Wavelet Network and Two-Dimensional PCA,” Suranaree Journal of Science and Technology, Vol.18, no.1, pp 436-445, 2011.

[19] Krebel, U., “Pairwise Classification and Support Vector Machines. Advances in Kernel Methods -Support Vector Learning”, Cambridge, MA, MIT, pp. 255-268, 1999.