

**HIGH-PERFORMANCE MULTIMODAL APPROACH
FOR DEFECT IDENTIFICATION IN KNITTED AND
WOVEN FABRIC**

Pallemullage Sajith Harshana Pallemulla

(188119K)

Degree of Master of Philosophy

Department of Computer Science and Engineering

University of Moratuwa

Sri Lanka

August 2022

**HIGH-PERFORMANCE MULTIMODAL APPROACH
FOR DEFECT IDENTIFICATION IN KNITTED AND
WOVEN FABRIC**

Pallemullage Sajith Harshana Pallemulla

(188119K)

Thesis submitted in partial fulfillment of the requirements for the degree Master of
Philosophy in Computer Science and Engineering

Department of Computer Science and Engineering

University of Moratuwa

Sri Lanka

August 2022

Declaration

I declare that this is my own thesis and this thesis does not incorporate, without acknowledgement, any material previously submitted for a Degree or Diploma in any other university or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Also, I hereby grant to University of Moratuwa the non-exclusive right to reproduce and distribute my thesis, in whole or in part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as articles or books).

Signature:

Date:

.....

.....

PSH Pallemulla

The above candidate has carried out research for the MPhil thesis under my supervision.

Signature of the Supervisor(s):

Date:

.....

.....

Dr. Chathura de Silva

.....

.....

Dr. (Mrs.) Sulochana Sooriyarachchi

Acknowledgements

This research was supported by the Accelerating Higher Education Expansion and Development (AHEAD) Operation of the Ministry of Higher Education funded by the World Bank.

I am extremely grateful to my supervisors, Dr. Chathura R. de Silva and Dr. Sulochana J. Sooriyaarachchi along with the deputy project coordinator of the FabVis project, Prof. Chandana D. Gamage, for their invaluable input and guidance throughout the research.

Abstract

Fabric inspection is a key quality assurance process in the garment industry as it involves the detection of defects in a fabric roll prior to being sent for production. Many studies have been conducted on defect identification in either knitted or woven fabrics, but only a few have considered both types. In this paper, a method for detecting defects in both knitted and woven fabrics is proposed. The method involves extracting co-occurrence, wavelet and local entropy features from a fabric image and classifying the image as defective or defect-free using a classifier with these features given as input. Five commonly-used classifiers were tested. This method was applied to a dataset with seventeen different types of defects and an overall classification accuracy of 93.31% was achieved by the k-nearest neighbours classifier.

Keywords:

fabric inspection, defect detection, co-occurrence, wavelet, local entropy

Table of Contents

Declaration	i
Acknowledgements	ii
Abstract	iii
Table of Contents	iv
1 Introduction	2
1.1 Background	2
1.1.1 Research Problem	3
1.1.2 Research Objectives	4
1.1.3 Research Contributions	5
1.2 Outline of Thesis	5
2 Literature Review	6
2.1 Fabric Defects	6
2.2 Fabric Inspection	7
2.2.1 Visual Fabric Inspection	7
2.2.2 Automated Fabric Inspection	8
2.3 Image Processing in Fabric Inspection	10
2.3.1 Challenges	10
2.3.2 Defect Detection Methods	11
2.3.2.1. Spatial Methods	12
2.3.2.2. Spectral Methods	17
2.3.2.3. Model-based Methods	22

2.3.3	Defect Classification Methods	25
2.3.3.1.	Statistical Inference	25
2.3.3.2.	Support Vector Machines	26
2.3.3.3.	Neural Networks	27
2.4	Summary	30
3	Methodology	31
3.1	Selection of feature extraction algorithms	31
3.2	Dataset Used	34
3.3	The Gray-level Co-occurrence Matrix	38
3.4	The Discrete Wavelet Transform	40
3.5	Local Entropy	42
3.6	Classification Algorithms	43
3.7	Summary	44
4	Feature Extraction and Defect Identification	45
4.1	Texture Feature Extraction	45
4.1.1	Selection of offset, orientation and features	46
4.1.2	Optimization of window size and gray level bit depths	50
4.1.3	Summary of Findings	52
4.2	Spectral Feature Extraction	52
4.2.1	Selection of wavelet function and mode of decomposition.	52
4.2.2	Optimization of vanishing moments and levels of decomposition	55
4.2.3	Summary of Findings	56
4.3	Entropy Feature Extraction	57
4.4	Feature Ranking	58
4.5	Defect Identification	59
4.5.1	Defect detection	59
4.5.2	Summary of Findings	60
4.5.3	Summary	60

5	Results and Discussion	61
5.1	Performance Metrics	61
5.2	Experimental Results	63
5.2.1	Results of texture feature optimization	63
5.2.2	Results of spectral feature optimization	70
5.2.3	Results of feature ranking	73
5.2.4	Results of defect detection	74
5.3	Performance Comparison	77
5.4	Summary	78
6	Conclusions and Future Work	80
6.1	Conclusions	80
6.2	Contributions	80
6.3	Future Work	81
	References	97

List of Figures

2.1	Categorization of fabric defect detection algorithms	11
2.2	Fabric defect detection using bilevel thresholding [1]. All defects appear as dark patches/lines on the light-coloured fabric. Notice how most of the defect in (b) is not detected due to its tapering ends not being adequately dark.	12
2.3	Defects from left to right: Colour Fly, Dirty Yarn, Hole, Oil Spot	13
2.4	Adaptive Local Binary Pattern (ALBP) on a square neighbourhood [2]	15
2.5	ALBP used on defective images. (a) original images, (b) images with 3x3 ALBP operator on 8x8 non-overlapping windows of the image, (c) images with 5x5 ALBP operator on 16x16 non-overlapping windows of the image [2]	16
2.6	A line-structural texture with dot-spot defect: (a) the original image: (b) the Fourier domain image: (c) the slope-angle histogram in the Hough space:(d) the notch that contains high-energy frequency components with frequencies manually set to zero: (e) the restored image: (f) the detected dot spots displayed as a binary image. [3]	19
2.7	Wavelet-based scheme for the detection and segmentation of fabric defects [4]	22
2.8	A typical backpropagation neural network used in defect detection [5]	28
3.1	General architecture of an image processing pipeline for image classification	31
3.2	Number of defects classified by each technique in past studies . .	32

3.3	Number of defects classified with the highest accuracy by each technique in past studies	33
3.4	Construction of the GLCM with $D = 1$ and $\theta = 0^\circ$	39
3.5	4 possible directions (θ), for $D = 4$	40
3.6	Filterbank representation of the wavelet transform (left) and the subband pattern (right) for one pass of the filterbank	41
3.7	Mallat (left) and packet (right) decomposition to four levels	42
4.1	Overview of the approach	45
4.2	Energy computed from the normalized GLCM	47
4.3	Contrast computed from the normalized GLCM	48
4.4	Correlation computed from the normalized GLCM	48
4.5	Energy and entropy computed from the normalized GLCM	49
4.6	Wavy knit fabric (left), satin fabric of uniform colour (middle) and wool fabric (right)	50
4.7	Experiment to select the optimal window size and gray level bit depth for the GLCM	51
4.8	Daubechies (db) wavelets with different numbers of vanishing moments	54
4.9	Experiment to select the number of vanishing moments and level of decomposition for the discrete wavelet transform	56
4.10	Local entropy feature extraction	57
5.1	F1 scores for the unsupervised detection with GLCM textural features	64
5.2	F1 scores per defect for the unsupervised detection with GLCM textural features	65
5.3	F1 scores for the supervised detection with GLCM textural features	66
5.4	F1 scores per defect for detection with GLCM textural features (unsupervised and supervised)	69
5.5	F1 scores for the supervised detection with wavelet features)	70

5.6	F1 scores per defect for detection with the db2 wavelet)	71
5.7	F1 scores per defect for detection with the db3 wavelet)	71
5.8	F1 scores per defect for detection with the db4 wavelet)	72
5.9	Average F1 score and average accuracy vs. number of neighbours (k) for the k-NN 5-fold cross-validation with the Manhattan dis- tance as the distance metric. The shading around the validation line plots show ± 1 standard deviation of the accuracy (in orange) and the F1 score (in blue).	76

List of Tables

2.1	Advantages and disadvantages of spatial methods	17
2.2	Advantages and disadvantages of spectral methods	23
3.1	Types of defects in the dataset	35
4.1	Mother wavelets used in research articles	53
4.2	Number of decomposition levels used in research articles	55
5.1	Selected parameters for the GLCM	70
5.2	Selected parameters for the discrete wavelet transform	73
5.3	Results of the feature ranking using Joint Mutual Information (JMI)	74
5.4	k-NN classification performance when features are removed from the bottom of the stack and when only the top features are used in the classification	75
5.5	Performance of different classifiers on the dataset	75
5.6	Performance of the k-NN classifier per defect	78