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Fabric Detectionusing various Techniques: A Review

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Abstract*-In the textile production, defect detection is an important factoron quality control process.Theinvestmentinautomatedtexturedefectdetectionbecomesmoreeconomical reducing labor cost. The cost of fabric is often affected bythe defectsoffabricsthatrepresentamajorproblemtothetextile industry. Manual inspections have the problems as lack of accuracy and high time consumption where early and accurate fabric defect detection is an important phase of quality control. Therefore automate fabric inspection i.e. computer vision based inspection is required to reduce the drawbacksdiscussedabove.Robustandefficientfabricdefect detection algorithms are required to develop automated inspection techniques. From last two decades so many computer vision based methods have been proposed. This paper attempts to categorize and describe these algorithms. Categorizationoffabricdefectdetectiontechniquesisusefulin evaluating the qualities of identifiedfeatures.*

Key Words: *fabric defect, automated visual inspection, quality control, defect detection, textile inspection*

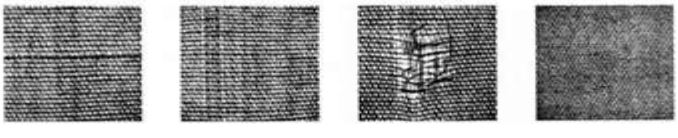
I. Introduction

ONE of the important aspects of the textile fabric is quality. To maintain the quality of fabric automated inspection system is required by the textile industry. Fabric defect detection system based on computer vision and artificial intelligence has been developed in the last 20 years. The significant advantages of the automatic defect detection system compared to human inspection are high efficiency, reliability and consistency [1].

It has been observed [2] that price of the textile fabric is reduced by 45% to 65% due to defects. Manual defect detectioninafabricqualitycontrolsystemisadifficulttask to be performed by inspectors. The work of an observer is verytediousandtimeconsuming.Theyhavetodetectsmall details that can be located in a wide area that is moving through their visual field. The identification rate is only about 70% [3]. Moreover, the effectiveness of visual inspection decreases earlier with the fatigue. Digital image processing techniques have been increasingly applied to textured sample analysis over the past several years. Nickoloy et al. [4] have shown that the investment in the automatedfabricinspectioniseconomicallyattractivewhen reduction in the personnel cost and associated benefits are considered.Textilequalitycontrolinvolves,amongother tasks,thedetectionofdefectsthatcauseadistortionoffabric structure of the material, which commonly shows a high degree of periodicity. Inspection of 100% of fabric is necessaryfirsttodeterminethequalityandsecondtodetect any disturbance in the weaving process to prevent defects from reoccurring.

II. Textiledefects

A portion of the textile fabric [5] that has not met the requirement or an attribute of a fabric is said to be a defect whichleadstocustomerdissatisfaction.Thefabricqualityis affected by yarn quality and loom defects. There are many kinds of fabric defects. Much of them caused by machine malfunctions and has the orientation along pick direction (brokenpickyarnormissingpickyarn),theytendtobelong and narrow. Other defects are caused by faulty yarns or machinespoils.Slubsaremostlyappearedaspointdefects; machine oil spoils are often along with the direction along the wrap direction and they are wide and irregular. An automated defect detection and identification system enhances the product quality and results in improved productivitytomeetbothcustomerneedsandtoreducethe costs associated with off-quality. Fig. 1 shows some examples of defects in various fabricmaterials.



(a) (b) (c) (d)

Fig -1: fabric defect samples: (a) double yarn; (b) missing yarn; (c) broken yarn; (d) variation of yarn

III. Fabric Defect Inspectionmethods

This section presents a literature survey on the prior techniquesandmodels,whichresearchershavebeenusing for fabric defect detection. On the basis of the nature of features from the fabric surfaces, the proposed approaches havebeencharacterizedintothreecategories[6];statistical, spectral and model-based.

1.1 StatisticalApproaches

Statisticalmethodsarebasedonthespatialdistributionof gray values [7]. In this method is that the statistics of the defect free regions are stationary and these regions extend over a significant portion of the inspection images. This approach is classified into first order (one pixel), second order (two pixels) and higher order (three or more pixels) statistics based on a number of pixels defining the local features.

1.1.1 Defect Detection using Morphological operations

Zhangetal.[1]haveintroducedthemorphologicalapproach todetectthedefects.Ithasbeenreportedinrecentpastthat the detection capability is greatly improved by rank-order filtering which is otherwise termed as generalized morphological operations. Mathematical morphology [18] extract useful component is an image for the geometric representation and description of regionalshape.

Erosion and dilation are two basic operations in morphological processing for smoothing, sharpening and noise removal. For erosion, the value of the output pixel is theminimumvalueoftheinputpixel'sneighborhood. For dilation,thevalueoftheoutputpixelisthemaximumvalue oftheinputpixel'sneighborhood.Pixel'sneighborhoodsare determined through structure element. It is a matrix consisting of only 0's and 1's that can have any arbitrary shape and size. The techniques used in morphological approach are basically nonlinear. The most successful method is an optimal morphological filter designed byMak etal.[18,19]forplainandtwillfabricdefectdetection.The method reached accuracies of 97.4% [18] and 94.87% [19] (offline detection). Mak et al. [19] further tested their approachonareal-timeinspectionwithdetectionaccuracy of96.7%.

1.1.2 Defect Detection using Bi-levelThresholding

Todetecthighcontrastdefectgraylevelthresholdingisvery simplemethod.Thepresenceofhighcontrastdefectcauses the received signal to rise or fall momentarily, and the resultantpeakandtroughcanbedetectedbythresholding. Stojanovic et al. [9] have invented a fabric defect detection method that uses thresholding with 86.2% of accuracy, but with 4.3% of falsealarm.

1.1.3 Defect Detection using FractalDimension

Fractals [20] are proficient and popular to model the statistical qualities like roughness and self-similarity on many natural surfaces. Fractal based methods use more features, both fractal and non-fractal, including fractal matrices[32],higherorderfractals[33].Thedifferentialbox

1.1.4 Defect Detection using EdgeDetection

Edge detection techniques are also very effective in detection of defects. Edges can be detected either as micro edges, using small edge operator masks or as macro edges, usinglargemasks.Thedistributionofnumberofedgesisthe important feature in texture images. In an image point, line and edge defects can be represented using number of gray level transition inan image[6].Thesefeaturescanbeusedto detect defects. But this method has also some drawbacks. This approach is only suitable to plain weave fabric images [6]. With these method defects nearby edges are hard to detect.

1.1.5 Defect Detection using Co-occurrencematrix

Co-occurrence matrix (CM) originally proposed by Haralicketal.[13], characterizestexture featuresassecond order statistics by measuring 2D spatial dependence of the gray values in a CM for each fixed distance and/or angular spatialrelationship.Co-occurrencematrixisthemostwidely usedmethod for texture classification. Ituses2Dmatricesto accumulate various texture features of images such as energy,contrast,entropy,correlation,homogeneityetc.[2]. These texture features are characterized as second-order statisticwhichisthemeasureofspatialdependenceofgray values for specific distance [3]. Haralick et al. [13] have derived14featuresfromtheco-occurrencematrixandused them successfully for characterization of texture such as grass,wood,Cornetc.LatifandAmetetal.[21,22]proposed the sub-band co-occurrence matrix (SBCM) method. They achievedadetectionaccuracyof90.78%.TheCMisinvariant under monotonicgray value in[7].Thespatialfeaturesofthe CM are superior to that of AF because the co-occurrence probabilities can extract more information in one spatial distance,whichisthemeasurebetweentwopixellocations. Connersetal. [14haveusedsixfeaturesoftheco-occurrence matrix, to identify nine different kinds of surface defects in wood. Rosler [15] has developed a real fabric defect detectionsystem,usingco-occurrencematrixfeatureswhich candetect95%ofdefects.Thesizeofco-occurrencematrix is important. So number of gray values must be reduced to meetthememoryrequirements[12].Ifthetexturefeatures are constructed using large sized primitive than this methods shows poor performance [3]. Two main weaknessesoftheCM[7]arepoorperformanceintextures constructedbylargesizedprimitiveandintensivecomputer requirements due to large number of adjacency pixel in calculation.

1.1.6 Defect Detection using Auto-correlation function

Auto-correlationfunctionmeasuresspatialfrequencyof image and it gives maxima of that frequency at different locations according to the length of repetitive primitive on image. These maxima will be constant for the primitive that hasbeenperfectthroughouttheimageanddifferentforthe primitives that are changed and imperfectin replication.Asa resultthoseprimitivescanbeconsideredasdefective[3]for fabricde fectdetection, Wood[7] utilized 2DAFtodescribe the translational and rotational symmetry of an image at plain carpet. However no explicit result was given. This method is mostly used for regular patterned images. It measures regularity and coarseness of pattern. But this method has limitation; it needs reference frame of tonal primitive to carry out analysis oftexture.

1.1.7 Defect detection using EigenFilters

The approaches based on this method are useful in separatingpairwise lineardependencies,ratherthanhigher orderdependencies,betweenimagepixels.Theinformation content of defect free fabric image can be extracted by registeringthevariationsinanensembleofmacrowindows withinthe image,independentofanyjudgmentofitstexture. UnserandAde[16],[17]usedthisinformationtoconstruct eigenfilters for defect detection in textured materials. The appearance based approaches using eigenfilters are highly sensitivetolocaldistortionandbackgroundnoise,therefore not attractive for online fabricinspection.

1.1.8 Defect Detection using Local Linear Transforms

To extract local texture properties some popular bidimensional transforms such as Discrete Cosine Transforms(DCT),DiscreteSineTransforms(DST),Discrete Hadamard Transforms (DHT), Karhunen-Loevetransforms (KLT),eigenfilteringcanbeused.Unser[23]testeddifferent local linear transforms for texture classification and found KLT as the best algorithm. Ade et al. [24] compared law filters, KLT,DCTandDHTfortextiledefectdetection.Intheir experiments, the KLT performance, particularly on larger windowsize,wasamongstthebest.Hadamardtransformis primarilydefinedforsizes,whichareinmultiplesoffour[6]. Neubauer [24] has detected fabric defects usingtexture energyfeaturesfromtheLawsmaskson10×10windowsof inspection images. In his approach three 5×5 Laws masks corresponding to ripple, edge and weave features [25] are usedtoextracthistogramfeaturesfromeverywindowofthe image. These features are used for the classification of the correspondingwindowintodefect-freeofdefectclass,using a three-layer neuralnetwork.

In online fabric inspection, the local transform such as DCT or DST can be directly obtained from the camera hardware using commercially available chips that perform fast and efficient DCT or DST transforms.

1.1.9 Defect Detection usingHistogram

Histogram properties include range, mean, harmonic mean, standard deviation, geometric mean, median and variance.Theseapproachesareinvarianttotranslationand rotation, and insensitive to spatial distribution of the color pixels.Duetothesefeaturestheybecomeidealfortheusein application [26,27]. Using statistics from localimageregions [27, 28], the accuracy of methods based on histograms can beimproved.Rankfunctionsandhistogramprovidesexactly same information [6]. Natale [29] has used rank order functionsforartificiallyintroduceddefectsdetectioninsome Brodatz textures [30]. Another method, cumulative histogram for the parquet slab grading is used by H. Kauppines [31]. The texture information about spatial distributionandorientation,etc.,isnotuniquelydetermined from the rank order functions [6]. Due to such drawbacks, rank functions or classical histogram analysis is not attractive for further interest for fabric defectdetection.

1.1.10 DefectDetectionusingLocalbinarypattern

T.Ojalaetal.[34]introducedtheLBPoperatorasashift invariantcomplementarymeasureforlocalimagecontrast. It usesthegraylevelofthecenterpixelofaslidingwindow asathresholdforsurroundingneighborhoodpixel.Usually the neighborhood is in circular form and the gray values of theneighborswhichdonotfallexactlyinthecenterofpixels are estimated by interpolation. Two dimensional distributions of the LBP and local contrast measures are used as texturefeatures.

1.2 SpectralApproaches

Spectral approaches are based on spatial frequency domain features which are less sensitive to noise and intensityvariationsthanthefeaturesextractedfromspatial domain. These approaches require a high degree of periodicitythus,appliedonlyforuniformtexturedmaterials. Such approaches are developed to overcome the efficiency drawbacks.Themainobjectiveoftheseapproachesisfirstly to extract texture primitives and secondly to modelorgeneralizethespatialplacementrules.Thesetechniquesare robust.

1.2.1 Defect Detection using FourierTransform

To characterize the defects Fourier transform uses frequency domain [3]. Fourier transform is derived from Fourier series [35]. This transform includes the properties like noise immunity, optimal characterization of periodic features and translation invariance. Fourier transform can becategorized in twocategories:DiscreteFouriertransform and Optical Fourier transform. Tsai and Heish [40] have detectedthefabricdefectsusingthecombinationofDFTand Houghtransforms[41].ChanandG.Pang[36]havegiventhe details of the usage of localized frequency components for therealfabric defect identification.Hofferetal.[37]hasused opticalFourierTransformtoidentifythedefects.Chiuetal.
[38] invented Fourier-domain maximum likelihood estimator (FDMLE) has given the significant result which wasbasedonafractionalBrownianmotionmodelforfabric defectdetection.
WindowedFouriertransform(WFT)issuggestedtolocalize and analyze the features in spatial and also in frequency domain. Campbell and Murtagh [39] have given the detail about WFT methods to detect the fabricdefects.

1.2.2 Defect Detection using WaveletTransform

Wavelet transform is a multiresolution algorithm and its multiresolution character corresponds to time–frequency multiresolution of human vision [42]. Shu-Guang and Ping- Ge[42]used wavelettrans form with BPneuralnetworkfor plainwhitefabric.Themultiscalewaveletrepresentationhas the property of shift invariance and can be used for fabric defect identification. The authors [43] have used lifting wavelet constructed by minimum texture entropy of DB wavelets and lifting scheme and were given the result over 95%. Guan, Yuan and Ke Ma [44] have developed a fabric defect detection system based on wavelet reconstruction with morphological filtering. Scharcanski [45] used the discrete wavelet transform to classify stochastictexture.

1.2.3 DefectDetectionusingGaborfiltertransform

Gaborfiltersareajointorspatial-frequencyrepresentation for analyzing textured images. Escofet et al. [47] described the fabric defect detection system based on asset of multi- scale and multi-orientation Gabor filters. Bodnarovaet al.
[48]inventedafabricdefectdetectionmethodinwhichaset of optimal 2D Gabor filters based on Fisher cost function is used. Zhang and Wong [49] applied a system based on 2D Gaborwavelet transformand Elmanneuralnetwork.Inthis system,thetexturefeaturesofthetextilefabricareextracted byusinganoptimal 2DGaborfilter. There cognitionrate was 100%.ShuandTan [46] proposed an algorithmbasedonmultichannelandmultiscaleGaborfiltering.Itwasbasedon the energy response from the convolution of Gabor filter banks in different frequency and orientation domains. The imaginary part of Gabor filter is odd symmetric, which is used to derive edge detectors [50] and the real part is even symmetric which is used to derive blob detectors[51].

1.3 Model-Basedapproaches

Texture can be defined by a stochastic or a deterministic model [6]. Model-based approaches are suitable for fabric images with stochastic surface variation. Autoregressive (AR) model belongs to 1-D class of stochastic modeling. Serafim [52, 53] applied a 2D AR model for texture representation. Forrealtimedefect detectiona1DARmodel is used in [54]. Cohen et al. [55] used Gaussian Markov RandomField(GMRF)tomodeldefectfreetextureoffabric images, whose parameters are estimated from the training samplesobservedatagivenorientationandscale.Campbell et al. [8] proposed model-based clustering to detect the defectsondenimfabric.Kongetal.[56]haveappliedanew color-clustering scheme for the detection of defects on colored random texturedimages.

IV. Conclusion

To ensure the quality level, 100% automated visual inspectionisnecessarytobe performed.Inthispaperabrief review of the of the automated fabric defect detection approaches is given with about 56 references. These techniquesarecategorizedintothreeapproaches:statistical, spectral and model-based. As the work is vast and diverse, the classifications for the automated fabric inspection approaches are improved. The fundamental ideas of these approaches with their disadvantages were discussed whenever known. To understand the formation and nature ofthedefects,itisimportanttobeabletoaccuratelylocalize the defective regions. Unfortunately, with these large numbersofimplementedapproaches,theperfectapproach does not exist yet as each of them have someadvantagesand disadvantages.The combination of the approachescangive the better results thanindividually.

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