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Novel Imaging Techniques for Woven Fabric based on the Weave Pattern

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Abstract:
India is known for its traditional culture. Next to agriculture, textile tradition is the second largest sector which creates more employment with high contribution towards Gross Domestic Product (GDP).The main goal of textile industry is to give a fault free product. In this work an analysis for the weaving pattern is given using image processing which enhances the products and produce the desired outcome. The work is computed for different algorithms such as structural analysis, centralized sparse approach, and the proposed decomposed sparsity.

Keywords: *Textile, Restoration, Sparsity, Woven Fabric,*

I. INTRODUCTION

Image processing is a methodology of performing some operations on an image, to enhance it and obtain some useful information as the result. It is also a type of signal processing [7], with image input, whose output are those image attributes dealing with processing of a digital system which supports the performance of the digitized image [1]. The performance generally relies on the acquisition and pre-processing, image analysis and manipulation, and displaying of information. The work is proposed is a trend setter between imaging sequence and textile processing. Generally in textile industries manufacturing process covers a range of production of raw material like natural and synthetic fibers including manmade ones also[13]. The Indian textile industry has reached a stronger position now compared to the last decades, with organized capital intensive production process including sectors as developed mills where advanced machineries of latest trends are utilized for mass production of textile products, and the unorganized dominating sector which uses traditional practices in cloth production with labor usage naturally. This industry is characterized by the production of clothes either through weaving or spinning with the help of hands. India's textile sector performance is next to China, which accounts 25% of the global trade. In India, there are about 1200 textile mills located all over the country contributing production from range of medium to large scale. The total cloth productions by handlooms are less when compared to power looms. Depending on the global market the man-made fiber, yarn filament, cotton yarn, blended, non-cotton yarn, etc., changes its productivity. The industry has about 34 million cotton spindles for cotton yarn manufacturing, which supports major part of India's textile exports. The domestic knitting industry is characterized by small scale units having facilities for dyeing, processing and finishing. This industry is concentrated on the production from Tirupur and Ludhiana. Tirupur, in the state Tamil Nadu concentrates on country's knitwear exports. The chart given below describes the details of year wise production of man-made fibre, filament yarn, cotton yarn, blended non-cotton yarn, total spun yarn in India in terms of Kilograms.

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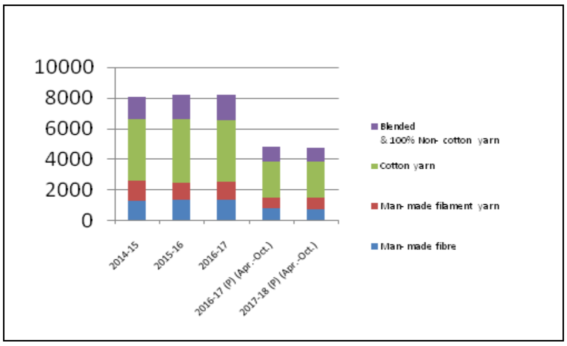

Figure 1 Production of materials from India(kgs)

The other chart given below provides the details of the overall mill sector decentralized sector and other cloth merchant sectors constructed in India (square feet values).

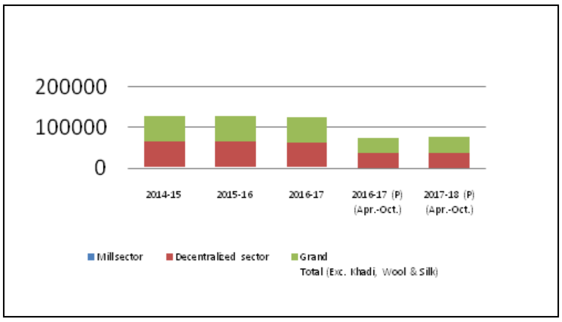

Figure. 2 Cloth merchant sectors (sqr.ft)

Specifically, Tamil Nadu a southern state of India, cities like Coimbatore, Erode, Gobichettipalayam, Perundurai and Tirupur, contributes a major part in the country's overall textile production.

II. RELATED WORKS

Many approaches have been proposed for textile processing from which few are discussed here. The quality of the fabric [10], is an important factor to be considered for better outcome. A method for Patterned fabric inspection has been proposed for fabrics which are plain and twill based on wavelet and neural network. Also spectral approaches like direct Thresholding, local binary pattern, gray relational analysis, and statistical and filtering approach like wavelet-preprocessing golden image subtraction, Bollinger Bands, and Regular Bands have been developed for inspecting complicated patterned fabrics [15]. The two approaches in fault detection methods a non-motif based and a motif-based approach proposed by Xie Xianghua which supports all topologies such as statistical, spectral and training. Statistical approach involves first order statistical measures and second order statistical measures defining features like directionality [6], roughness, linearity and density, and boundaries within the space, but it also has some difficulty in identifying the defects [9]. The spectral approach includes Fourier, Wavelet and Gabor transforms describing directionality of line patterns, where the defects appear as irregularities. The wavelet and Gabor filters by Aabouelala are used for spatial frequency analysis with reduced data size and defects. Further the combination of the Gabor wavelet features [11], has been proposed for twill fabric detection, but not suitable for all forms of defects. To overcome the limitations of standard Wavelet Transform, Adaptive Wavelet Transform has been proposed to obtain best results if the defect type is known in prior. A Gabor filter scheme has been proposed as a suitable class of representations like statistical, structural, filter based methods, and model based approaches, to inspect textural abnormalities. Also Gray-level statistical and morphological methods have also been proposed using localization and intensive computations, to view the high degree of periodicity for textile fabrics, to compare manual and automated inspections [2]. The fabric performance is determined on theoretical bases, which needs experimental set up to meet the working conditions [12], which tends to loss of time and high expensive recycled wastes. Fabric Fault Detection Using Digital Image Processing has been proposed on computer vision, using histogram equalization and binary conversion and finally the features are being extracted with more accuracy &efficiency. Fabric defects detection and sorting using image processing has formulated a SVM approach for garment industry. Here a genetic algorithm for SVM classifications of a trained set of acquired defect samples, to detect and classify the defects of high quality image samples is proposed. Automatic fabrics fault processing [8], using image processing technique is used where a threshold value has been set for the feature classification using histogram equalization. The defects are removed using classical noise removal technique.

III. NON LOCAL AUTOREGRESSIVE MODELING

When natural images are processed, many nonlocal similar patches give a constraint to the local structure. Non-local autoregressive model is proposed and taken as the data dictionary term, which can effectively reconstruct the edge structure and ringing artifacts. Interpolation methodology help in recovering by continuous convolution using the smoothing function which extracts the model, assuming that the low resolution is directly down sampled from the original high-resolution, involving in recovering the missing pixel, from the noisy or disturbed one, which is computed by forming weighted average of surrounding values. The structure is a natural extension and generalization of the regressive models which use only the spatially local neighbor pixels for approximation, which is repeated until desired value is obtained. Sampling matrix induced by the model is less coherent with representation dictionary and consequently makes more effective for image interpolation and reconstruction. Non local model improves the interpolation and the observation model by incorporating the similar constraint. Other than local redundancy, the natural images which are considered also have an abundant amount of non local redundancy. The pixel may have many non local neighboring pixels which are similar to each other. There occurs a method of iteration for the obtaining model. Such procedure is iterated until the desired estimation of the reconstructed is capture Depending on the image the segregation the type may be global or local, where single threshold is applied for local and different set is applied for global type, based on the neighboring pixels [14]. The useful information is extracted by the automatic threshold technique, an effective tool to distinguish the images which are encoded into pixels to minimize the background noise, accomplished by utilizing a feedback loop which optimizes the threshold value thus converting the image into two parts: the background and foreground. Initially automatic threshold value is set for original, then it is partitioned into two portions as less than or equal to the set value and other greater, finally the average of the mean is obtained. The input image is down sampled to reduce the operational constraints after which it is scaled and formatted for the desired operation. There occurs an interpolation problem during this formatting process. To overcome this interpolation issue, the method of bi-cubic interpolation is employed, which has no reconstruction at the non-local neighboring pixel. The Non local Model technique is employed for obtaining a reconstructed image. The acquired reconstructed one is then compared with the input. On the comparison made, if the expectation is not obtained, then it is interpolated with the proposed methodology Iterations are repeated for different values to meet the closer original image as shown in the below flow chart.

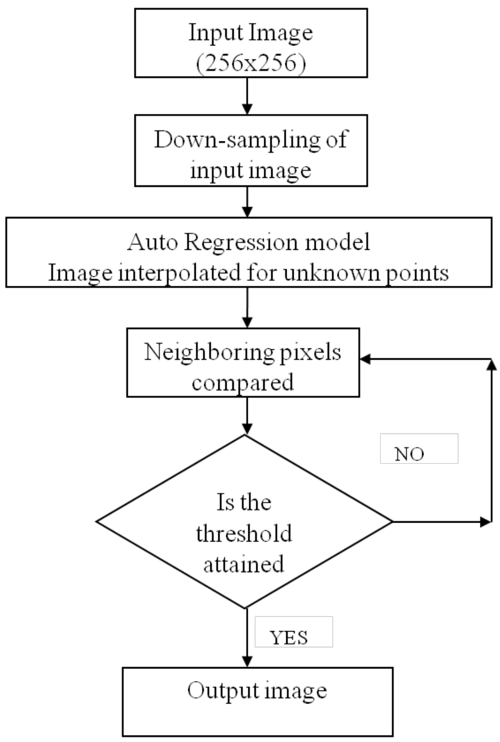

Figure 3 Flowchart of Non Local Modelling

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Table1 PSNR values of different interpolation techniques

Interpolation Types					
Initial	Cubic	Linear	Spline	Nearest	Makima
3.9	3.78	24.05	23.57	24.45	24

The table shows the different PSNR values of initial, cubic, linear, spline, nearest and makima interpolation methods.

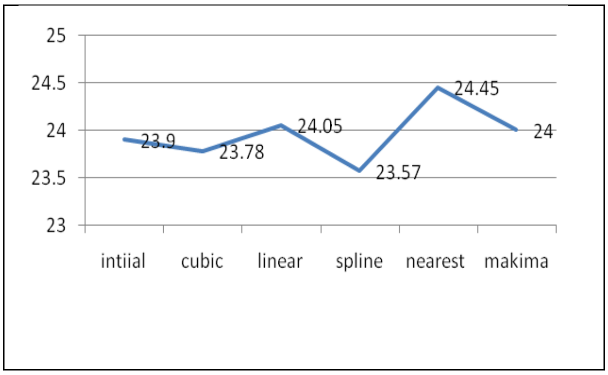

Figure 4 PSNR comparison of the interpolation methods

IV. SPARSE REPRESENTATION BASED RESTORATION

A common dictionary 'B' is assumed which is linear self-adjoint and positive operator with an observation vector 'y' of unknown class as a linear combination of training vector. Now with the class of 'BS' the minimum value of unique point can be reached. The function to be minimized is:

$$\lambda \| g - Au \| + (u) \qquad (1)$$

Let u> 0; so u$\|A * A\|$< 1, and $B =$ u$A * A$, Combining the minimization with the dictionary the samples of kth class, the test image will lie approximately in the linear space of training samples from the class k. This implies most coefficients will be close to zero. Here 'A' implies the sparse vector. To represent the observed vector y in sparse vector 'A', the following equation

$$y = B*A \qquad (2)$$

An effective CSR has been proposed which overcomes the local and non-local redundancy to produce effective results in image restoration techniques [3]. The general formulation of revamping for the proposed work using degradation model can be given as:

$$y = Hx + v \qquad (3)$$

where the H is the degradation matrix, x is the original image, v is the noisy one. This regularization technique moves with the processing of all raw images in reality. Sparse technique is one of trendy approach which can deal with all these problem formulations [4]. The centralized sparse representation model has used two parameters to balance the local and non-local redundancy. This has produced an improving convergence speed and good image restoration quality. The main parameter has been determined using Bayesian Interpretation, producing the relation between the Bayesian and Wavelet Interpretation. The images are considered to be matrices with N rows and M columns. Wavelet decomposition is used, at every level the horizontal data is filtered, which produces the approximation, the vertical, the horizontal and the diagonal detail at every sub-level. Usage of minimum number of pixels constitutes the sparsity signals. The work is based on the combination of these two techniques as shown in the Figure 5 below

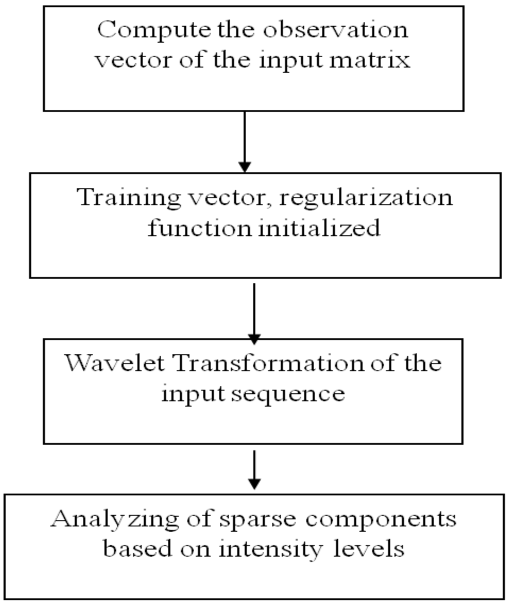

Figure 5. Flow Chart of sparsity technique

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The input sample is converted under a threshold value, further the vertical, horizontal and diagonal decomposition are made using wavelets, under a sparse kernel so as to minimize the usage of approximations, and the processed outputs which are sparsely decomposed are also displayed in the figure below

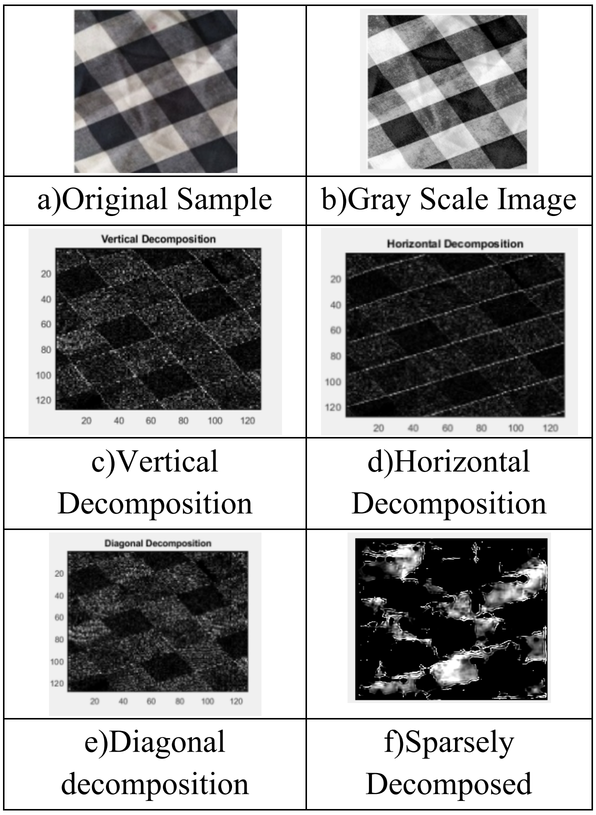

Figure 6(a)Original Sample ,(b) Gray Scale Image, (c) Vertical Decomposition , (d) Horizontal Decomposition, (e) Diagonal Decomposition ,(f) Sparsely Decomposed

The figure 6(c-e) shows the different level of decomposition of images using wavelet and the 6f image shows the sparsely decomposed image.

Table.2 PSNR values of different decomposition

Type of Decomposition	PSNR of Blurred image	PSNR of Restored image	Computation Time
H	20.89846	22.18332	1.778033
V	18.9299	19.76521	4.874517
D	18.85837	19.64656	4.836617

Similarly the different PSNR values of horizontal, vertical, and diagonal decompositions are tabulated along with the respective computational time.

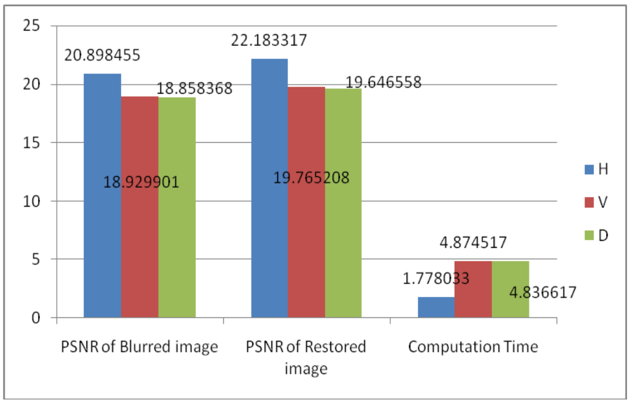

Figure 7. PSNR CHART comparison of H,V,D

The comparison of the PSNR values of horizontal, vertical and diagonal decomposition using wavelet for the sample1 is given in the figure 7, describing that the horizontal approximation has maximum PSNR whereas diagonal has minimum value.

Table 3 Simulation results of sparsely decomposed sample

PSNR Value	SSIM	Mean Square Error
19.65	0.1026	150.75

The value of SSIM, and MSE is also tabulated to measure the performance of the test sample, and the values are given in the table3. The calculation of PSNR values for structural approach, centralized sparse approach, wavelet based approach, with the proposed super resolution and decomposed sparsity techniques.

Table 4. PSNR comparison of all methods

	Structural Approach	Super resolution	Wavelet based approach	Decomposed Sparsity
PSNR Value	22.52	29.12	30.12	19.65

V. CONCLUSION

The work can be summarized as that the main objective is to develop a method to decrease the faults in weaving technology. The super resolution technique has been proposed, where based on the Thresholding value the images are subjected to different interpolation methods, whose PSNR values are calculated and compared. The sparsity normalization and the Sparse with wavelet decomposition technique has been proposed so as to reduce the pixel rate while processing, whose degree of restoration has been compared based on Horizontal, Vertical and Diagonal decompositions.

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