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Fuzzy Logic Forge Filter Weave Pattern Recognition Analysis on Fabric Texture

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Abstract: In today's textile industry, the evaluation of fabric texture properties still relies on manual operations with the help of microscopes, which are very tedious and time consuming. Developments in computer vision technology led to an increased research effort in image texture analysis for a large variety of applications, such as surface roughness inspection in manufacturing, texture classification, defect recognition for textile quality control, medical image inspection shape recognition and liquid depth measurement. The surface roughness measurement of the fabric can be carried out using various methods. Fractal dimension is a parameter frequently used to analyze surface roughness. The fractal dimension measurement is based on 2D-FFT which is scale-invariant and rotation-invariant. The computer simulated fabric images and real woven scanned fabric images are used to demonstrate that FD-FFT using Fuzzy logic with 3D visualization and interpretation provides a fast and reliable parameter for fabric roughness measurement.

Keywords: 2D-FFT, Fuzzy Logic, Surface Roughness, Fractal Dimension

1. Introduction

1.1. Digital Image Processing

Digital image processing is the use of computer algorithms to perform image processing on digital images. An image may be defined as a two-dimensional function, f(x, y), where x and y are *spatial* (plane) coordinates, and the amplitude off at any pair of coordinates (x, y) is called the *intensity* or *gray level* of the image at that point. When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. Digital image processing allows the use of much more complex algorithms, and hence, can offer both more sophisticated performance at simple tasks [1] and the implementation of methods which would be impossible by analog means. In particular digital image processing is used for classification, feature extraction, pattern recognition, projection and multi-scale signal analysis.

1.2. Fabrics

Fabric is a cloth produced especially by kitting, weaving or felting fibers. The weaving of cloth is exclusively a human characteristic and is a feature of most human society. Woven fabrics are highly structural materials, having their appearance and handling and mechanical properties influenced by their geometric structure [10]. They are formed by two sets of mutually perpendicular and interlaced yarns:" warp and weft". Warp refers to the long vertical yarns that are warped around the looms. Weft refers to horizontal yarns that are woven through the warp yarns. The weave pattern and the yarn count are two major geometric characteristic of woven fabrics. Weave pattern refers to the basic unit of weave that is periodically repeated throughout the entire the fabric area. Yarn count is defined as the number of yarns per centimeter. The weave pattern and the yarn count are the characteristic that affect the dynamic behavior of the fabric.

2. Surface Roughness Measurement of Weft Knitted Fabrics

Surface Roughness measurement of weft knitted fabrics using image processing published in (1990 in which Kawabata evaluation systems for fabrics (KES-F) is time consuming and the transaction of the data measured is difficult. It is a contact method more easily affected by environmental conditions, not suitable as an on –line system in manufacturing process. Surface roughness of knitted fabrics without any deformation was measured by a non-contact method using a high resolution scanner [7]. The data was controlled on a computer by using MATLAB software to data in the roughness index. The results were compared with KES-F systems holds a good correlation between fabric roughness value measured by the two method. A negative correlation coefficient shows that the roughness values measured by Kawabata changes reversely proportional to those measured by the image processing method using fuzzy logic techniques as shown in figure 1.

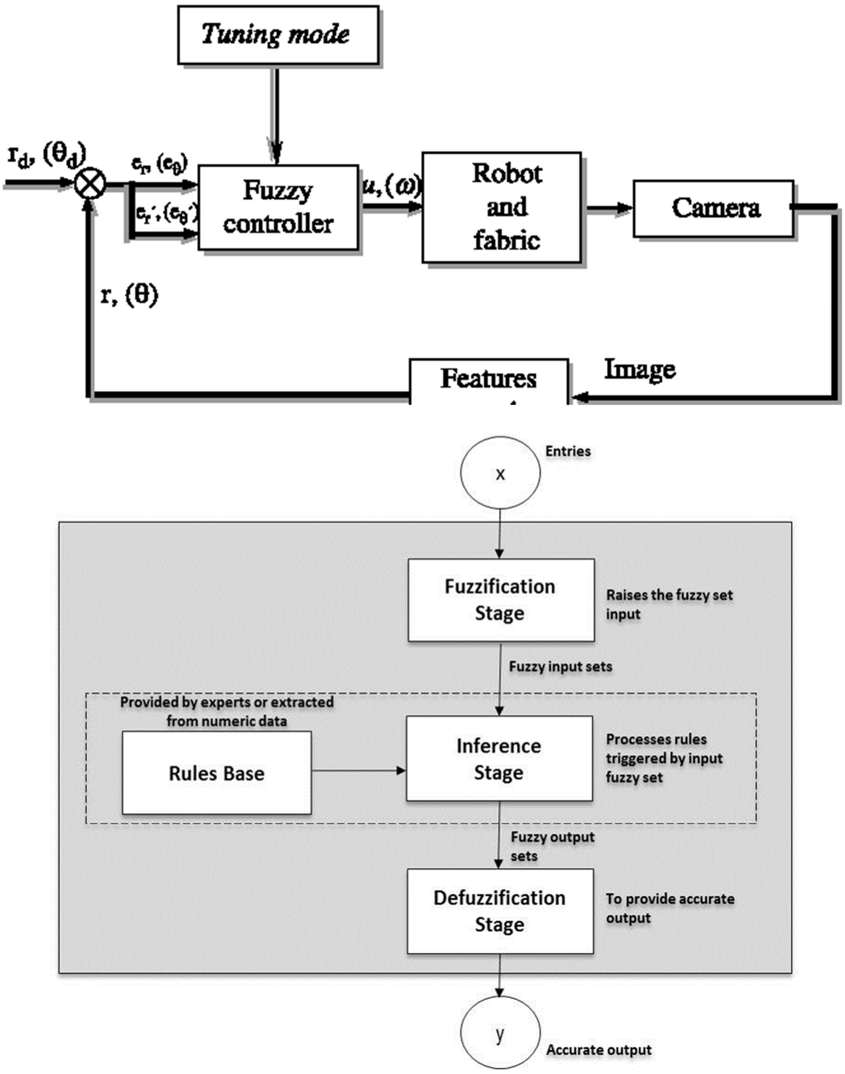


Figure 1. *Implementation of fuzzy logic for pattern recognition.*

2.1. Surface Roughness Measurement for Textile Fabrics

Surface roughness measurement for textile fabrics by a non-contact method for tactile perception proclaimed in 1992 in which measurement of surface roughness applied the KES-F which is contact method disturbs an accurate measurement for analysis of tactile perception [3, 5]. Measure the roughness of textile fabrics without deformation by a non-contact method applied the laser displacement sensor with the resolution of item and a accuracy of 0.01% and high precisely controlled linear motor for translated at constant speed. Analyze the effect of colour and luster in order to reduce the optical errors. The data is controlled on computer and executed FFT by using MATLAB for obtain roughness, the mean values and mean deviation. The perception data histograms are consistent with the group in the misclassification.

2.2. Performance Evaluation for Motif-Based Patterned Texture Defect Detection

Performance evaluation for motif-based patterned texture defect detection discussed in 1994 shows that co-occurrence matrices (CM) highlights the spatial properties on texture by gray level spatial dependence such as uniformity of energy, correlation, maximum probabilities, homogeneity and inertia [2]. The main weakness of CM approaches is the intensive computation. Wavelet preprocessed Golden image subtraction (WPGIS) method gives the best detection success rate with moving average and standard deviation. Circular shift operation is used sucte that motif based method does not consider spatial relationship between pixels which resulted in the problem of defective motif hawing similar histogram characteristics. Global transform offers a joint spatial and spatial frequency representation for different scales and multi orientations. A wavelet bases are shift invariant and the wavelet descriptors rely on pattern location, difficult to describe a texture pattern from wavelet inefficient as shown in figure 2.

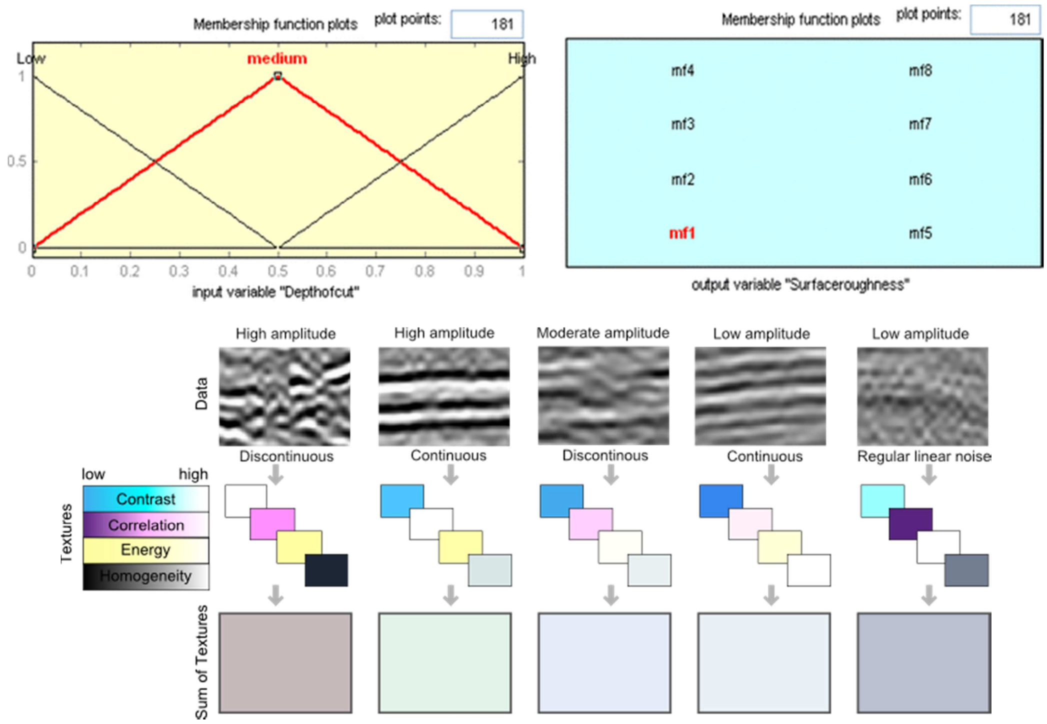


Figure 2. *3D seismic visualization and interpretation.*

3. Computer Vision Based Fabrics Defect Detection

A survey in 199 shows that inspection method using imaginary Gabor functions and linear neural network have been aptly developed for low resolution images. Fabric defect detection by the usage of a fuzzy wavelet analysis technique using fractal scanning but his appropriate cannot detect defect that appears as subtle change in fabric texture [4, 9]. Estimate of fractal dimension on inspection images to detect fabric defects, based on differential box counting method to minimize computational complexity and to entrance efficiency. Spatial Gray level dependence matrix (SGILDM) Gray level Run Length Matrix (GLRLM) the major problem in the conventional use of the co-occurrence matrix in fabric defect detection are inefficient portioning of co-occurrence space and inefficient description of multi pixel co-occurrence. The localization accuracy of the detected defect is very poor and have high false alarm.

4. Bayesian Classification of Fabrics Using Binary Co-Occurrence Matrix

It is developed in 2000 shows that fabric texture feature is extracted using Gray Level Co-occurrence Matrix as well as Binary Level Co-occurrence Matrices. The co-occurrence matrices functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image and then extracting statistical measures from this matrix [2]. The extracted feature from GLCM and BLCM used to classify the texture by Bayesian classifier to compare their effectiveness. The texture analysis has already been applied to fabric recognition but it still cannot recognize all type of fabrics and texture through computer vision.

4.1. Application of Computer Vision in The Automatic Identification and Classification of Woven Fabric Weave Pattern

It is developed in the year 2001 reveals that the fabric image to find out the warp and weft by the pixel gray-level cumulative values, It then cut out the image of the wrap and weft floats to obtain the texture feature values, and use the Fuzzy-C Means (FCM) algorithm to identify the warp and weft floats. The identification results can derive the black-white digital image and the digital matrix of the fabric weave pattern. Finally, weaves classification is conducted based on the successfully trained two-stage Back-Propagation Neutral Network. This two-stage network can be used to construct the computer vision system to recognize fabric texture, and to increase the system reliability and accuracy. This study used the first-order and second-order Co-occurrence matrix, and confirms that fabric patterns can be identified and classified accurately with this method. This may lead to misjudgment and is limited by the optical environment attesting, as well as the appearance differences of fabrics and yarns. The first-stage Back Propagation Neutral Network can accurately classify 18 fabric weave pattern of 9 types with an identification rate of 100 percentages [8]. The active grid model (AGM) to identify the texture of fabrics, but the error of the overall identification by the self-adjusting matching is still high as shown in figure 3.

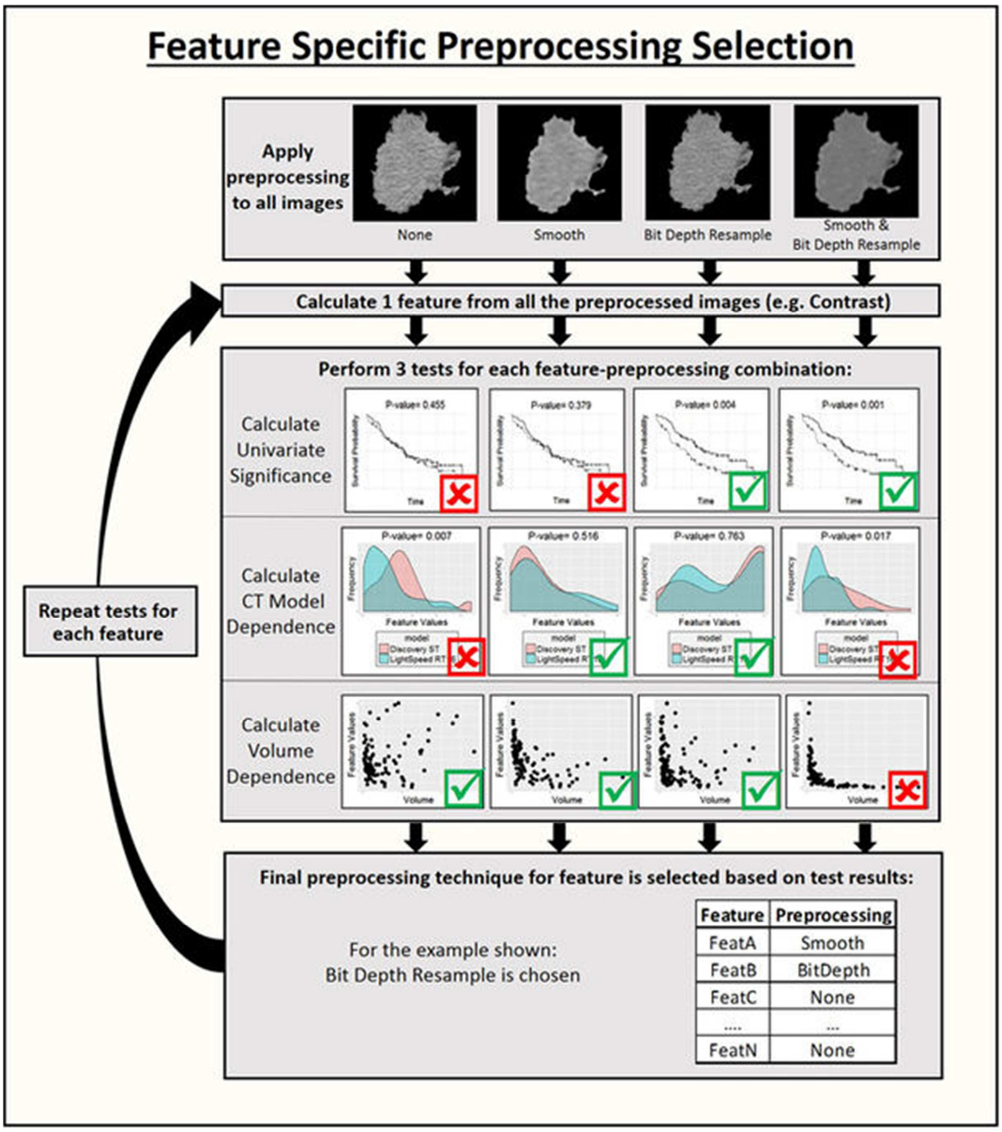


Figure 3. *Feature specific preprocessing selection.*

4.2. 3D Geometric Modeling of Hand-Woven Textile

It is developed in the year 2001 describes the geometric model would be superimposed by a haptic model, a fuzzy rule based algorithm is applied to the still images of the artifacts to generate the 3D model. The derived model is exported as a 3D VRML model of the textile for visual representation and haptic rendering [6]. Various methods such as neural networks, fuzzy logic and Fourier image analysis techniques have been applied to still images of the textile artifact with varying degrees of success. The major drawback of such methods has been the rigidity of the models identified for the artefacts. A recursive backtracking procedure is developed to add a feature point to yarn edge set *warp* and *weft* by employing the Fuzzy Rule-Based Engine. Developing a generic algorithm to construct the haptic model of the textile and superimposing it on the geometric model is another major step in the future work. This will require both the development of the software driving the haptic model and the hardware providing tactile interface between the user and the model [7]. This will reveal the changes required to improve the accuracy and effectiveness of the algorithm as shown in figure 4.

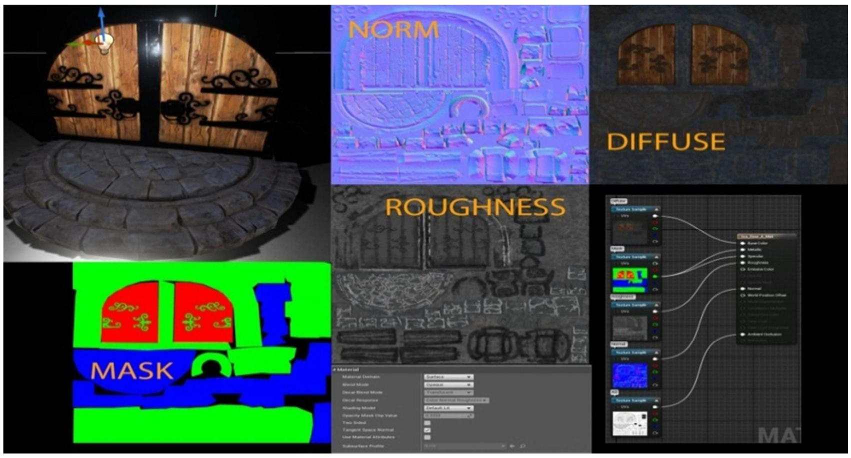


Figure 4. *3D geometric model generator in pattern recognition stage.*

4.3. Texture Based Pattern Classification

It is proclaimed in 2002 shows that the features used in the project are standard deviation and entropy of all parts obtained after 3rd level decomposition using discrete wavelet transform (DWT) [8]. A mean feature vector is calculated and is used for classification. For classification distance similarity is used. Most natural surfaces exhibit texture and successful vision system must be able to deal with textured world surrounding it. The mean feature vector (MFV) is derived from this crop, which indicates one class. Thus we have ten classes and the problem is to find to which class the query image belongs so that complexity decreases to 35%. The texture discrimination approaches are ad-hoc. Texture is an innate property of virtually all surfaces the grain of wood, the weave of fabric, the pattern of crop in fields etc. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment.

5. Surface Roughness Measurement

Fabric structural patterns have huge influence on surface roughness which is an important parameter for mechanical comfort. The structural pattern of textile fabric depends on the appearance of weft and warp on the surface. Modern methods are based on the image processing of surface images of fabric. The surface irregularity of plain textiles has been identified by friction, a contact blade, lateral air flow, a step thickness meter or subjective assessment [6]. Three dimensional surface roughness data can only be acquired by doing multiple scans of the fabric surface. It is slow and needs a complicated operation of the instrument. Therefore, the trend to use the noncontact method of surface roughness assessment on the 3-D surface data is inevitable and beneficial. Noncontact surface roughness measurement is faster than the traditional stylus-based method with high accuracy and is particularly nondestructive. Fractal dimension is a parameter frequently used to analyze surface roughness. Fractal dimension is obtained by aggression modeling of coefficients in horizontal and vertical directions with respect to the decomposition levels as shown in figure 5.

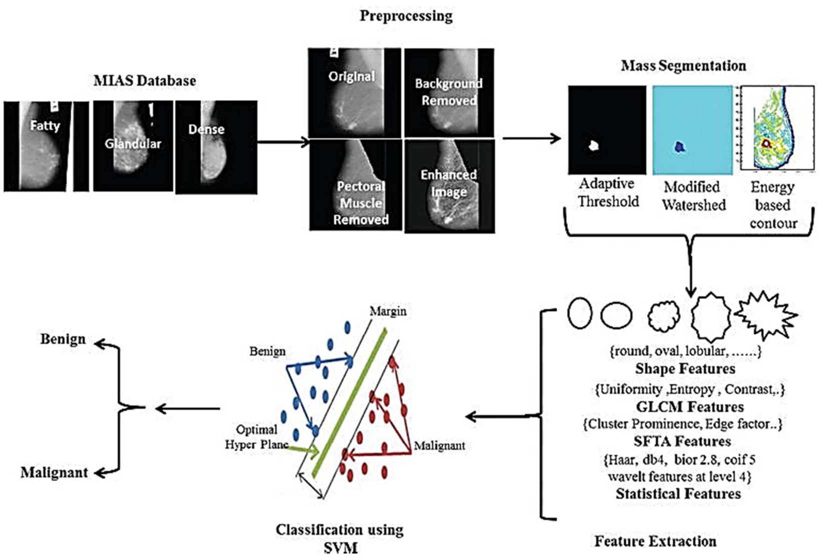


Figure 5. *Feature extraction based on GLCM, SFTA using SVM for benign and malignant.*

5.1. Proposed Work

The Fourier analysis allows the characterization of repeated patterns in their cross direction and their uniformity in the machine direction. For characterization of roughness of textile surface, the Mean Absolute Deviation (MAD) is usually applied. It is similar to the SMD as per Kawabata. In the proposed work the parameter called fractal dimension is used. The fractal dimension measurement based on 2DFFT analysis of fabric images is a scale-invariant and rotation-invariant parameter to evaluate the surface roughness of fabrics. The proposed system extends 2DFFT-based fractal method to 3-D surface data, which are obtained from high-resolution 3-D laser scanning. The general idea is that the image (*f(x, y)* of size *M* x *N*) will be represented in the frequency domain (*F(u, v)*). The equation for the two-dimensional discrete Fourier transform (DFT) is:

$$F(u,v) = \sum M - 1 \sum N - 1 f(x,y)\, e\hat{}(-i2\pi\{(ux/M) + (vy/N)\})$$

The basic concept behind Fourier transform is that any waveform can be constructed using a sum of sine and cosine wave of different frequencies. The exponential in the above formula can be expanded into sine and cosines with the variables u and v determining these frequencies. The values of Fourier transform are complex, meaning they have real and imaginary parts. The imaginary parts are represented by –i. Fourier transform is computed as Fourier spectrum and display it as an image. For images MATLAB use 2DFFT and FFT is used more for audio.

5.2. Estimation of Fractal Dimension

The power spectrum $P(\omega)$ is proportional to the certain power β of the radial frequency ω, i.e., $P(\omega) \propto \omega{-}\beta$ where$\beta \geq 0$. The fractal dimension (*FD*) of an image is related to the exponent β in above equation, i.e. $FD_{\mathrm{FFT}} = 8 - \beta 2$ where FD_{FFT} denotes our fractal dimension estimate based on 2DFFT. The general algorithm of our fractal dimension estimation is as shown in figure 6. Three-dimensional points of the fabric surface are gathered from 3-D laser scanning with very high resolution up to 1 μm. The raw 3-D data consist of a large number of 3-D coordinates. By applying the 2DFFT, the information is transformed to the spatial frequency domain. The power spectrum is calculated to remove the imaginary part of the 2DFFT result. According to the properties of Fourier transform, theoretically, this measurement is robust to linear translations and scaling.

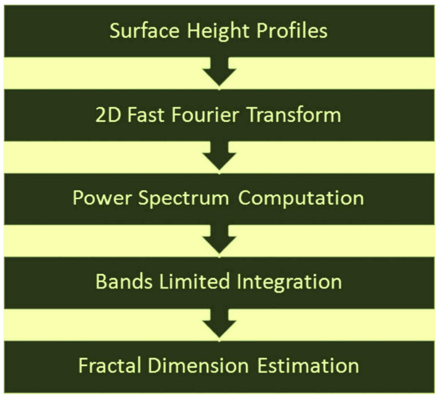
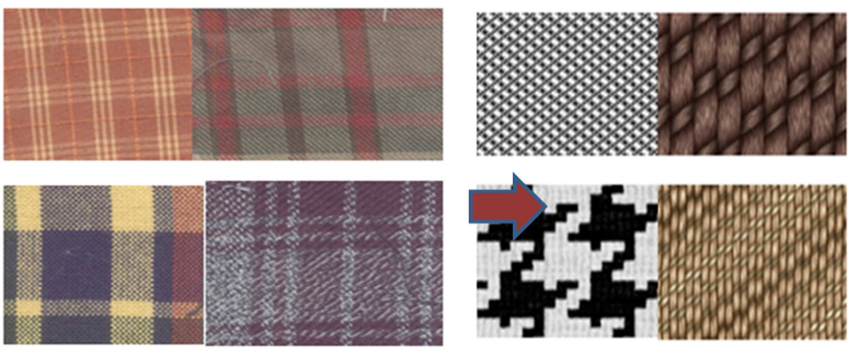


Figure 6. *General steps in Fractal dimension measurement.*

6. Simulation Result and Discussion

6.1. Surface Roughness Measurement Experiment

To validate the goodness of *FD*FFT as a parameter for evaluating fabric surface roughness and to demonstrate the robustness of our fractal dimension measurement *FD*FFT, we used computer-simulated fabrics that were generated using Forge filter. The input image is initially converted into a gray scale image and 2-D FFT is applied to the obtained gray scale image. The power spectrum of the image is calculated from its magnitude and phase spectrum. The gray image is binarized and fractal dimension is calculated from which the surface roughness of the fabric is obtained as shown in figure 7a, 7b.



a b

Figure 7. *a. Original fabric images, b. Forge filter generated gray images.*

The structure of a hand-woven textile sample is not always linear, and exposes some degree of non-linearity, randomness and uncertainty. A generic methodology based on fuzzy rule-based and Fourier image analysis is developed for automatic nondeterministic pattern recognition of the woven fabrics. All possible conditions are checked in the fuzzy rules including negative gradients, zero gradients and positive gradients. A 3D geometric model generator is developed to produce an accurate VRML 3D model of the textile based on the data obtained in pattern recognition stage as shown in figure 8, 9. Success rate is approximately 84 percentage by using the extraction and calculation of summary statistics of the GLCM found in Grey Scale images, having an advantage in speed compared with other method. Based on the good acceptance of GLCM approaches compared to texture recognition, in this research GLCM is used as the basis for textile recognition. GLCM based texture recognition has been used in combination with other techniques, including combining its statistical features with other methods such as genetic algorithms. By matching the test image with Bayesian classifier, the type of the fabric is identified. Based on the results observed, BLCM method performs well when compared to GLCM.

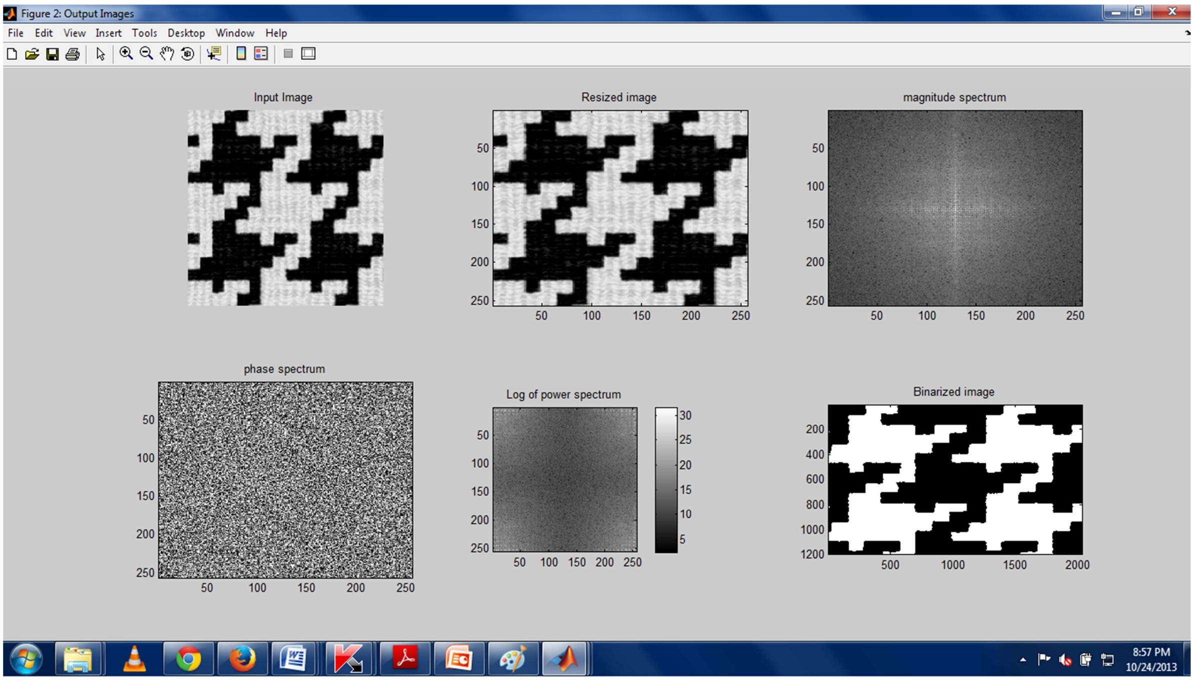
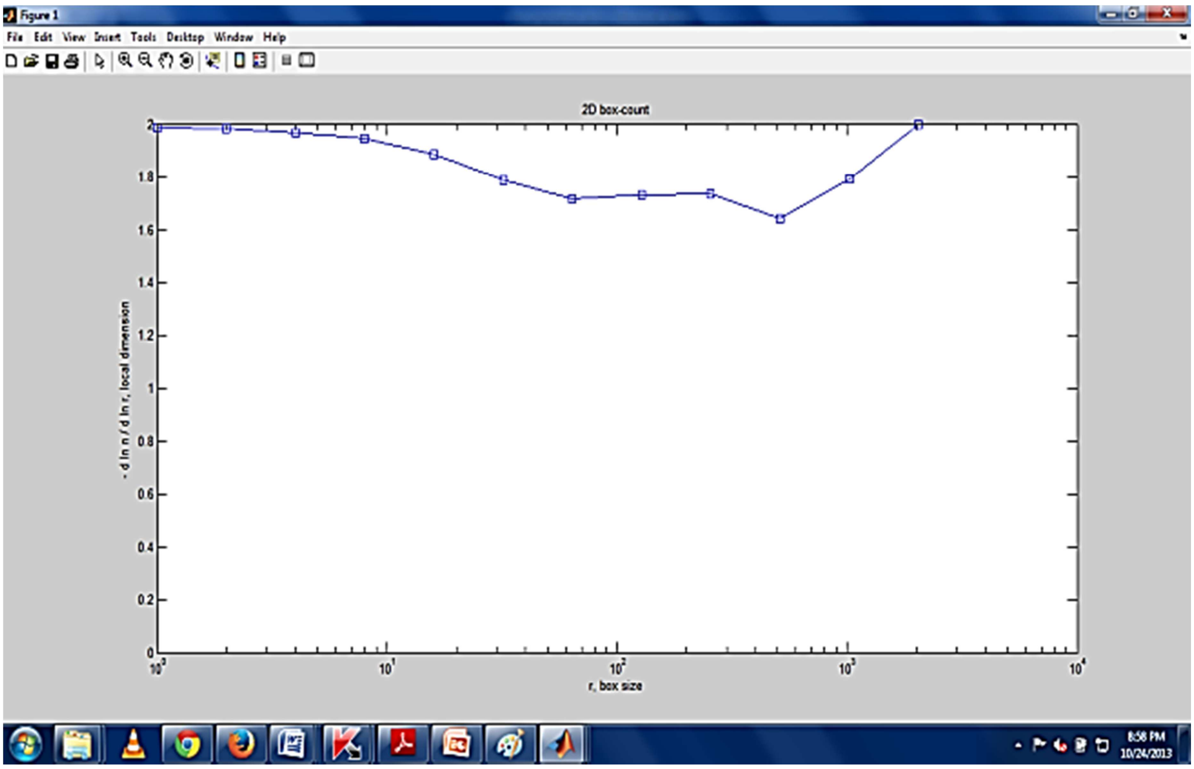


Figure 8. *Output of the forge filter generated images gives log of power spectrum, binarized image, magnitude and phase spectrum.*



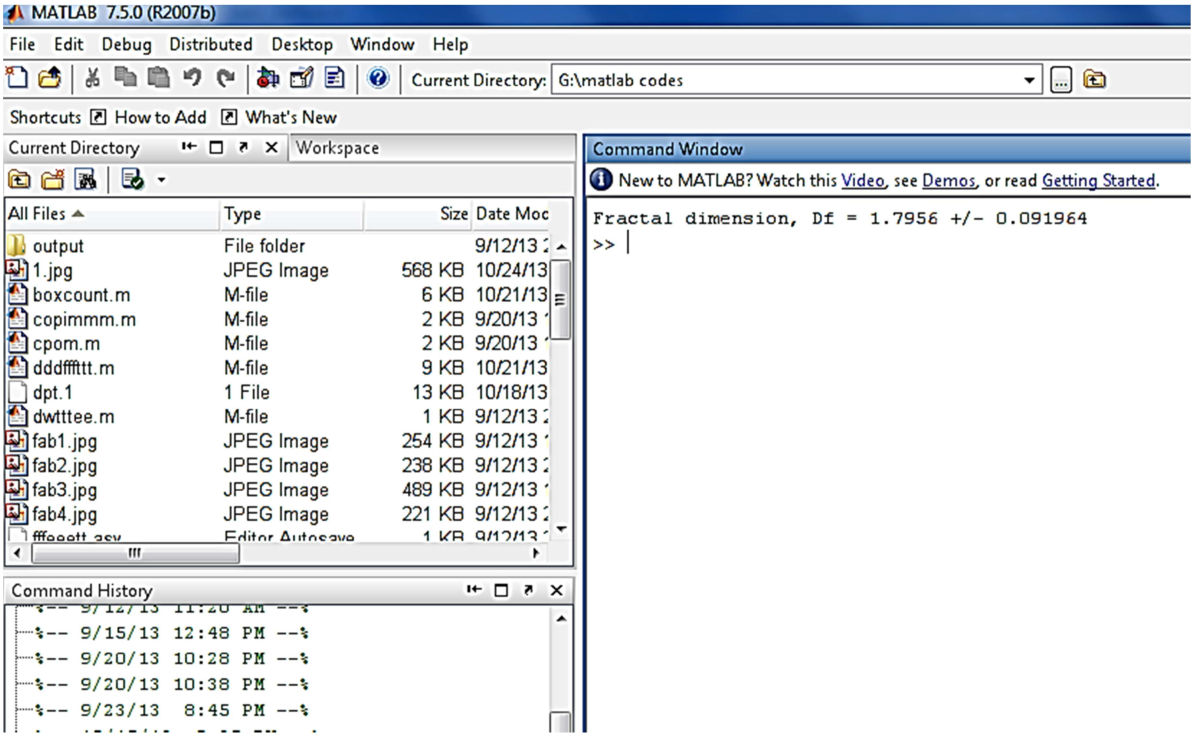


Figure 9. *Box count and fractal dimension values for the forge filter generated images.*

6.2. Conclusion

It can be concluded that a noncontact surface roughness measurement is faster than the traditional stylus-based method with high accuracy and is particularly nondestructive. The non-contact method of surface roughness assessment on computer simulated fabric. The rotation invariance and scale invariance of FD_{FFT} were validated with fractal Brownian images. It was found that the proposed 2-D FFT algorithm using fuzzy logic membership tuning rules provides fast reliable parameter evaluation for fabric surface roughness using Fuzzy logic technique in MATLAB platform results in enhanced performance about box count of 12769 with fractal dimension values of 1.7956+/-0.091964 for woolen fabric with 3D visualization and interpretation. On comparison with feature extraction based on GLCM, SFTA along with SVM, 2DFFT with Fuzzy logic combined with Forge filter gives better result in surface roughness measurements.

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