Comparison of Performances of Spectral Based Approaches on Fabric Defect Detection

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ABSTRACT
In this paper, it is aimed to compare the performance of spectral based fault detection methods in quality control by testing on the same environment. The most widely used spectral based approaches as Fourier Transform, Wavelet Transform, Gabor Transform were used to extract features of the faulty fabric samples. By using statistical functions feature selection was done so huge dimensionality of features was decreased. The selected features are taken as inputs for feed-forward network (with the back propagation algorithm) to classify faulty fabrics in categories; weft, wrap and oil. All computations were performed in Matlab program so as to satisfy all conditions as the same. The analyses’ results show the Wavelet transform in terms of classification for three type defects was more efficient than the others, on other hand; Fourier transform in terms of processing time is faster than the others.

Keywords—fabric detection techniques, Fourier transform, Wavelet transform, Gabor transform, classification defects

I. INTRODUCTION
Inspection of fabric defects is vital in terms of quality control due to reliability, accuracy and production cost in textile industry. Human vision quality control can be effective in detecting distinctive faults. However, a trustable, objective and stable automatic quality control is necessary to increase the accuracy of inspection of fabric defects and to decrease the production cost instead of human vision control. In despite of that it is not possible 100% defect free fabric production; the defect level can be decreased to minimum with the automatic control. In past years, for automatic fabric defect detection, statistical, spectral, model-based, structural and neural network approaches were performed. In these approaches, spectral based detection methods got more importance than the others because; they especially enable to detect small defects on fabrics. The mostly used spectral based approaches are Fourier, Wavelet and Gabor transform.

It is seen that Fourier transform among spectral based approaches firstly was used for detection [1-4]. Campbell et al. [5] implemented Fourier transform with an 11 layer NN. Campbell and Murtagh [6] used windowed Fourier transform on denim fabrics. In [7, 8], for fabric defect detection and Fourier transform was compared with K-L transform. The researchers implemented Fourier transform on real fabric images for four type defects by selecting two central spatial frequency spectrums from a 3D Fourier frequency spectrum [9, 10]. A Fourier analysis model was proposed by Tsai and Hu [11] on four different types of fabric defects including missing end, missing pick, broken fabric and oily fabric. Millán and Escofet [12] introduced Fourier-domain-based angular correlation to identify similar periodic patterns, even though the defective fabric sample image was rotated and scaled. Baştürk et al. [13] used Fourier transform, thresholding and Gabor filtering for 9 type defects. Zhao et al. [14] proposed Fast Fourier transform and self-adaptive spectrum. Mean and standard deviation values of local energy were used to get feature vectors. Jayashree and Subbaraman [15], researched Fourier power spectrum and morphologic filters to get periodical features of fabrics.

By using wavelet transform, Sari-Sarraf and Goddard [16] improved a vision based fabric defect inspection system which has a success rate 89% all over small fabric defects. D. Karras [17] has developed a new method based the Discrete Wavelet Transform Analysis and the Support Vector Machines (SVM) classification. Zhi et al. [18] applied adaptive wavelet to detect fabric defects for inspection. Serdaroglu et al. [19] proposed a novel solution combining ICA and wavelet concepts. This solution showed that implementing wavelet analysis before
ICA raised the fabric defect detection rate measured up to the wavelet transform and ICA alone. Latif-Amet et al. [20] used co-occurrence matrices and MRF (Markov Random Fields) by obtaining features from wavelet decomposed image. Jasper et al. [21, 22] applied wavelet analysis. Yang et al. [23] detailed adaptive wavelet- from single adaptive wavelet to the multiple adaptive wavelets. The results showed 98.2% success rate in the detection of 56 faulty fabric images including eight types of defects and 64 defect free ones. In reference [24], the study which was performed by using wavelet transform for the inspection of 45 defective fabric samples showed 100% accuracy rate. Liu and Qu [25] performed wavelet transform (db5 wavelet) on 30 images and succeeded classification at 95% rate using back-propagation NN. Guan and Shi [26] got a 92.5% success rate analyzing fabric images with db1, db2, db3 db4 wavelet at first level. Han and Shi [27] proposed a novel approach based on co-occurrence matrices extracted from approximation sub-band images. Jiang et al. [28] proposed optimal wavelet transform tree. The study was done with entropy and energy values of the sub-band images. Liu et al. [29] performed a classification on nonwoven fabrics using wavelet texture analysis and LVM. Su et al. [30] obtained a 96.5% success rate using wavelet energies and backpropagation NN. Guan [31] performed a one level transform for normal faults and multiple levels transforms for small defects on 160 fabric images. He classified them over 95% by using features as standard deviation, entropy, energy etc. Liu et al. [32] studied on nonwoven fabrics using wavelet energy and Bayesian NN. The 18 characteristic features of images obtained from third level decomposition provided a 98% success rate, additionally 24 features obtained from fourth level decomposition raised success up to 99%. Liang et al. [33] achieved 90% classification success rate by using discrete wavelet, statistical measurement and Fuzzy NN.

In reference [34-36], a Gabor filter family was used by tuning to several resolutions and orientations for texture segmentation. Kumar and Pang [37] performed fabric defect detection using only real Gabor functions. Shu et al. presented a method for automatic fabric defect detection based upon multi-channel and multi-scale Gabor filtering [38]. Han and Zhang [39] proposed Gabor filter masks to detect fabric defects. Arivazhagan and et al. [40] applied Gabor wavelet transform to detect fabric defects. In reference [41], an odd symmetric real-valued Gabor filter were presented. In the study, overall recognition accuracy was 96.2% on 39 defects samples. Baştürk et al. [42] used Gabor wavelet filtering and reduced features vectors with PCA. Liu et al. [43] performed feature extraction in both time and frequency domain using Gabor filtering to detect defects. Mak and Peng [44] performed online fabric defect detection. They used Gabor wavelet network and caught a success rate 96%. In reference [45], the proposed approach was based on Gabor filter masking and morphologic filtering for adaptive thresholding. Zhang et al. [46] combined Gaussian and Gabor transform and achieved classification of 360 defective images at 87% success rate. Chen et al. [47] used thresholding, standard deviation and fusion, which were obtained from coefficients of applied Gabor filtering for defect detection. Zhang et al. [48] introduced a real defect detection system for cord fabric. Using Gabor transform online and offline defect detection testing gave good performance and correct results.

In literature, previous studies show that fabric defect detection and classification were performed by using some spectral based methods for different fabric samples. However; the same data (fabric samples) should be used to determine objectively which method supplies best performance in terms of the ability of detection and process time. In this study, the methods were compared in the same environment (computer, program etc.) by using the same fabric samples. Hence, the most suitable method amongst the three methods for online fabric defect detection was searched.

II. MATERIAL AND METHODS

In this study, fabric images were taken by using a camera with proper lightening conditions and then the images were transferred into computer for further image processing operations. These images in the spatial domain were transformed into the spectral domain using spectral based transforms in Matlab program. The flowchart of the fabric defect detection is shown in Fig.1.
II. Feature Extraction

II.1 Fourier Transform

With Fourier series any periodic function or signal can be expressed as the sum of the series of sine and cosine wave in varying amplitudes and frequencies. The Fourier transform in image processing gives an image as a sum of complex numbers of varying magnitudes, frequencies, and phases. Fourier transform helps to investigate the image characteristics in the frequency domain. So, the Fourier transform in image processing applications such as image analysis, enhancement etc. has a significant importance. If \( f(m,n) \) is a function of two discrete spatial variables \( m \) and \( n \), then the two-dimensional Fourier transform of \( f(m,n) \) is defined by the relationship in the equation 1:

\[
F(w_1, w_2) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} f(m,n) e^{-jw_1m} e^{-jw_2n} \tag{1}
\]

The variables \( \omega_1 \) and \( \omega_2 \) are frequency variables; their units are radians per sample. \( F(\omega_1, \omega_2) \) is often called the frequency-domain representation of \( f(m,n) \).

In general, since Fourier transform computationally lasts long, fast Fourier transform (FFT) is used to decrease the process time. FFT is a reformed algorithm of discrete Fourier transform which may computationally save lots of time. In our study, after the faulty images were converted into gray-level, they were split into 256×256 pixels sub-images because image width and length ought to be power of two for FFT which we used to enable fast computation. After FFT computation, the magnitude of frequency spectrum was used to select feature vectors because it does not change when the fabric is moved up. The spectrum is only varied by the change of fabric structure [9].

![Image Acquisition](image.png)

Fig. 1 The fabric detection schema.

![Original Image and Transformed Image](image.png)

Fig. 2 (a) shows original image and (b) shows a representation of the Fourier transform by applying a logarithmic transformation because normally the dynamic range of the Fourier coefficients is too large to be displayed.

II.1.2 Wavelet Transform

The wavelet transform provides powerful insight into an image’s spatial and frequency characteristics at multiple resolutions [49]. The wavelet transform, a mathematical tool developed by Mallat[50], is particularly well adapted to the use of wavelet bases in image processing. Wavelet transform is decomposition of a signal with the orthogonal basis functions. Two functions exists; the mother wavelet and scaling function [51]. So as to construct the mother wavelet in the wavelet transform the scaling function \( \Phi(x) \) is firstly determined (eq. 2)

\[
\Phi(x) = \sqrt{2} \sum_{k} h(k)(2x - k). \tag{2}
\]

The mother wavelet \( \psi(x) \) is generated by using the given equation above.
\[ \psi(x) = \sqrt{2} \sum_{k} g(k)(2x - k) \]
where \( g(k) = (-1)^k h(1 - k) \) \( (3) \)

The mother wavelet, shown as \( \psi(x) \), is got through translation and dilation of the function.

\[ \psi_{m,n}(x) = 2^{-m/2} \psi(2^{-m} x - n) \]
where \( m \) and \( n \) are integers. Since \( \psi_{m,n}(x) \) forms an orthonormal basis,

\[ c_{m,n} = \int_{-\infty}^{+\infty} f(x)\psi_{m,n}(x)dx \]
and the wavelet decomposition is then

\[ f(x) = \sum_{m,n} c_{m,n} \psi_{m,n}(x) \]

In the decomposition, the scaling function and the mother wavelet functions needn’t to be computed; transform coefficients can be obtained by the functions \( h(k) \) and \( g(k) \) recursively. A decomposition at \( J \)-level can be expressed as

\[ f(x) = \sum_{k} c_{0,k} \phi_{0,k}(x) \]

\[ = \sum_{j} \sum_{k} c_{j+1,k} \phi_{j+1,k}(x) + \sum_{j} \sum_{k} d_{j+1,k} \psi_{j+1,k}(x) \]

(7)

where the coefficients \( c_{0,k} \) are given at the scale \( j \) + 1, the coefficients \( c_j \) and \( d_j \) are associated to the coefficients \( c_n \) at the scale \( j \) through

\[ c_{j+1,n} = \sum_{k} c_{j,k} h(k - 2n) (0 \leq j \leq J) \]
\[ d_{j+1,n} = \sum_{k} d_{j,k} g(k - 2n) (0 \leq j \leq J) \]

(8)

(9)

The meaning of these expressions in signal processing is that to obtain \( c_{j \cdot} \) and \( d_{j \cdot} \) at resolution \( j+1 \), coefficients \( c_j \) and \( d_j \) at level \( j \) is to be convolved with the functions \( h(n) \) and \( g(n) \). Decomposition in the conventional wavelet transform scheme that is also called pyramid structured wavelet transform. The completion of the process, the output of \( J \)-level decomposition is obtained the low-resolution coefficient \( c_{J,n} \) and detail coefficients \( d_{J,n} \) for each level \( j \). (Fig.3)

In the image processing, 2-D wavelet that is an expression of the 2-D basis functions with two 1-D wavelet basis functions. The low-resolution coefficient \( c_{j,n} \) and detail coefficients \( d_{j,n} \) needn’t to be computed; transform coefficients can be obtained by the functions \( h(k) \) and \( g(k) \) recursively. A decomposition at \( J \)-level can be expressed as

\[ f(x) = \sum_{k} c_{0,k} \phi_{0,k}(x) \]

\[ = \sum_{j} \sum_{k} c_{j+1,k} \phi_{j+1,k}(x) + \sum_{j} \sum_{k} d_{j+1,k} \psi_{j+1,k}(x) \]

where \( c_{0,k} \) are given at the scale \( j \) + 1, the coefficients \( c_j \) and \( d_j \) are associated to the coefficients \( c_j \) at the scale \( j \) through

\[ c_{j+1,n} = \sum_{k} c_{j,k} h(k - 2n) (0 \leq j \leq J) \]
\[ d_{j+1,n} = \sum_{k} d_{j,k} g(k - 2n) (0 \leq j \leq J) \]

Symlet wavelet 2 (sym2) (Fig. 4) from wavelet families was used at level 4 for analysis, the approximation coefficients at level 4 and the detail coefficients at level 1,2,3,4 were used for this paper. The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. When a 256×256 pixels image was decomposed, 129×129 pixels approximation image (A1),129×129 pixels horizontal detail image (HD1), 129×129 pixels vertical detail image (VD1) and 129×129 pixels diagonal detail image (DD1) were obtained, the next process composes 4×66×66 pixels decomposed images - A2,HD2,VD2,DD2 and so on.(Fig.5).
II.1.3 Gabor Transform

Gabor filters have been widely used in image processing applications. The Gabor transform provides an effective way to analyze images and has been elaborated as a frame for understanding the orientation and spatial frequency selective properties of images. D. Gabor [52] firstly defined the 1-D Gabor function and Daugman [53] extended that to a 2-D filter later. The expression of the Gabor filter mathematically is

\[ G_{\sigma, \phi, \theta}(x, y) = g_{\sigma}(x, y) \cdot \exp\left[2\pi j\phi (x \cos \theta + y \sin \theta)\right] \]  \hspace{1cm} (10)

where

\[ g_{\sigma} = \frac{1}{2\pi\sigma^2} \exp\left[-\frac{x^2 + y^2}{2\sigma^2}\right] \] and \( j = \sqrt{-1} \) \hspace{1cm} (11)

The parameters of a Gabor filter are given by the frequency \( \phi \), the orientation \( \theta \) and the scale \( \sigma \). The Gabor filter \( G_{\sigma, \phi, \theta}(x, y) \) forms complex valued function. Each of the complex Gabor filters has the real and imaginary parts that are conveniently implemented as the spatial mask of \( N \times N \) sizes. The Gabor filter \( G_{\sigma, \phi, \theta}(x, y) \) decomposes into real and imaginary parts:

\[ G_{\sigma, \phi, \theta}(x, y) = R_{\sigma, \phi, \theta}(x, y) + jI_{\sigma, \phi, \theta}(x, y) \] \hspace{1cm} (12)

where

\[ R_{\sigma, \phi, \theta}(x, y) = g_{\sigma}(x, y) \cdot \cos[2\pi \phi (x \cos \theta + y \sin \theta)] \]
\[ I_{\sigma, \phi, \theta}(x, y) = g_{\sigma}(x, y) \cdot \sin[2\pi \phi (x \cos \theta + y \sin \theta)] \] \hspace{1cm} (13)

The filtered output of the image is got by the convolution of the image \( f(x, y) \) with the Gabor filter \( G_{\sigma, \phi, \theta}(x, y) \), as following

\[ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \cdot GG_{\sigma, \phi, \theta}(x, y) \, dx \, dy \] \hspace{1cm} (14)

In this study, the faulty fabric images were convolved with the created Gabor kernels at eight orientations (0, 45, 90, 135, 180, 225, 270, 315 degrees) and two phases (0, 90 degrees). After convolution, 16 filtered images were obtained. Fig. 6 shows the original image (a) and the Gabor filtered images (b) at 0, 45, 90, 135 degrees. The convolution results for the given orientations can be combined in a single output image. Using the L2, L1 or L-infinity norms, the combination is able to be made in different ways. This is called superposition of phases, here, this paper used L2 norm to combine the filtered images in a single image. In L2 norm, the squared values of the convolution results for the concerned orientation are added together pixel-wise and followed by a pixel-wise square root computation. Fig. 7 shows the fabric image (a) and the combined image with L2 norm (superposition) (b).
II.2 Feature Selection

Feature selection is a process to reduce feature vector dimension selecting the most identifier ones for classification. In order to select features, some statistical functions are generally used. In the study, median, mean, max, min and standard deviation were used as statistical functions.

For Fourier transform, feature selection was done in that way: The magnitude of frequency spectrum was computed from each transformed fabric image with FFT. The obtained coefficient matrix from magnitude is normally 256×256 matrix. By applying these statistical functions as rows-wise, these features (coefficients) were reduced to 1280×1.

For wavelet transform, feature selection was done in that way: After performing wavelet transform for each fabric image up to level 4, the detail coefficients of each level sub-images and fourth level approximation coefficients consists of 129×129×3+66×66×3+34×34×3+18×18×3 matrices and 18×18 matrix respectively. The horizontal, vertical and diagonal detail coefficients of each level -for example, HD1, VD1, DD1, HD2, VD2, DD2 etc. were decreased to 789×1 by computing standard deviation as rows-wise and other statistical functions as normal (two dimensional). Finally, fourth level approximation coefficients (A4) were added to those, so the feature vectors to be used becomes an 1113×1 (324+789) matrix.

For Gabor transform, feature selection was done in that way: The Gabor features of the image were obtained by convolving the image with the family of Gabor filter kernels. The filtering at eight orientations generates 8×[256×256] filtered images. With superposition technique these images were reduced to 256×256 (fig. 7). By applying these statistical functions as rows-wise, these features (coefficients) were reduced to 1280×1.

The selected features (feature vectors) were kept for further processing (they all will be provided for the feed-forward network inputs).

II.3 Classification of Fabric Defects with Feed-forward Networks

Feed-forward networks were introduced as models of biological neural networks [54], in which neurons and edges corresponded to synapses, and with an activation function $g(a)$ given by a simple threshold. With the recent developments, feed-forward networks have widely proceeded in almost all fields and especially for pattern recognition and classification. A feed forward network with back propagation algorithm is a supervised and a fast neural network in terms of execution speed. For this reason, this network can be chosen for the classification of faulty fabrics pattern. A feed forward network simply consists of one input layer, one or more hidden layers and an output layer. Feed forward neural network architecture is shown in Fig. 8.

![Feed forward neural network architecture](image)

Fig. 8 Feed forward neural network architecture

A feed-forward network (FNN) can be viewed as a graphical representation of parametric function which takes a set of input values and maps them to a corresponding set of output values [55]. Here, inputs are transformed into hidden layers’ neurons and the inputs values are computed with bias and some weights to find new weight in neurons. Each neuron
performs a weighted summation of the inputs, which then passes a nonlinear activation function \( g(a) \), also called the neuron function\(^{[56]} \). In detail, the output of the \( k^{th} \) hidden node is obtained by first forming a weighted linear combination of the \( n \) input values \( x_i \) to give equation as following:

\[
y_k = \sum_{i=1}^{n} w_{ki} x_i + b_k
\]  

(16)

The value of hidden variable \( k \) is then obtained by transforming the linear sum using an activation function \( g(y_k) \) to give equation below:

\[
z_k = g(y_k)
\]  

(17)

Tan-Sigmoid transfer function used in the feed forward network can mathematically be expressed as;

\[
g(y_k) \equiv \tanh(y_k)
\]  

(18)

Finally, the outputs of the network are obtained by forming linear combinations of the hidden variables to give equation below:

\[
y_j = \sum_{k=1}^{n} w_{jk} z_k + c_j
\]  

(16)

Here, \( w_{ki} \) and \( w_{jk} \) are the weight parameters, \( b_k \) and \( c_j \) are the bias parameters and together they constitute the adaptive parameters in the network.

A feed forward network with back-propagation algorithm was used to classify the faulty fabric patterns in this study. The specifications of the built FNN using Artificial Neural Network Toolbox of MATLAB are given in Table 1.

<table>
<thead>
<tr>
<th>Model</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>No of Hidden Layer</td>
<td>1</td>
</tr>
<tr>
<td>Neurons of Hidden Layer</td>
<td>260</td>
</tr>
<tr>
<td>Activation of Hidden Layer</td>
<td>Tan-sigmoid</td>
</tr>
<tr>
<td>Neurons of Output Layer</td>
<td>3</td>
</tr>
<tr>
<td>Activation of Output Layer</td>
<td>Tan-sigmoid</td>
</tr>
<tr>
<td>Validation Ratio</td>
<td>% 10</td>
</tr>
<tr>
<td>Test Ratio</td>
<td>% 10</td>
</tr>
</tbody>
</table>

### III. RESULTS AND DISCUSSION

In this study, 25 real faulty fabric images with different types of defects; wrap, oil and weft defects were used to compare the performances of spectral based approaches. Fig. 10 shows three types of defective fabric samples. When applying Fourier transform to the real defective fabric images, the coefficients that have real and imaginary parts were obtained. Then the magnitude of frequency spectrum was computed because the magnitude doesn’t change when image moves. The magnitude coefficients can be given into the network as inputs; however, the more number of inputs for the networks causes network to run slowly due to heavily computation in the network. On the online defect detection system, the time has a vital importance for all of image processing applications; therefore, feature selection was preferred to reduce features. Feature selection was applied to Fourier, Wavelet and Gabor transform features for further process (classification) as explained previous section. Table 2, 3, 4 shows the obtained feature vectors of three defect types as sample.
Fig. 10 Wrap, Oil and Weft faulty fabric images in size 256x256 px

Table 2 Fourier transform Feature vectors

<table>
<thead>
<tr>
<th>Fabric Images</th>
<th>Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
</tr>
<tr>
<td>Wrap Defective Fabric</td>
<td>325.9578</td>
</tr>
<tr>
<td>Oil Defective Fabric</td>
<td>248.575</td>
</tr>
<tr>
<td>Weft Defective Fabric</td>
<td>724.3228</td>
</tr>
</tbody>
</table>

Table 3 Wavelet transform Feature vectors

<table>
<thead>
<tr>
<th>Fabric Images</th>
<th>Coefficients (for first level)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
</tr>
<tr>
<td>Wrap Defective Fabric</td>
<td>129.8427</td>
</tr>
<tr>
<td>Oil Defective Fabric</td>
<td>219.6842</td>
</tr>
<tr>
<td>Weft Defective Fabric</td>
<td>275.8225</td>
</tr>
</tbody>
</table>

Table 4 Gabor transform Feature vectors

<table>
<thead>
<tr>
<th>Fabric Images</th>
<th>Coefficients (for first scale and first orientation)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
</tr>
<tr>
<td>Wrap Defective Fabric</td>
<td>6.536469</td>
</tr>
<tr>
<td>Oil Defective Fabric</td>
<td>2.479286</td>
</tr>
<tr>
<td>Weft Defective Fabric</td>
<td>79.16018</td>
</tr>
</tbody>
</table>

Lasted time for computation of Fourier, Wavelet and Gabor transform and feature selections of them were held as shown in Table 5. When compared to each other, it is clearly seen that Fourier transform runs faster than the other transforms. On the hand, Gabor transform is slower among all transforms.
Table 5: The elapsed time for transforms and feature selection

<table>
<thead>
<tr>
<th>Fabric Images</th>
<th>Time in seconds</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fourier</td>
<td>Wavelet</td>
<td>Gabor</td>
</tr>
<tr>
<td>Image 1</td>
<td>0.1275</td>
<td>0.0272</td>
<td>1.0723</td>
</tr>
<tr>
<td>Image 2</td>
<td>0.0276</td>
<td>0.0256</td>
<td>0.9597</td>
</tr>
<tr>
<td>Image 3</td>
<td>0.0102</td>
<td>0.0266</td>
<td>0.9510</td>
</tr>
<tr>
<td>Image 4</td>
<td>0.0102</td>
<td>0.0254</td>
<td>0.9521</td>
</tr>
<tr>
<td>Image 5</td>
<td>0.0103</td>
<td>0.0261</td>
<td>0.9490</td>
</tr>
<tr>
<td>Image 6</td>
<td>0.0100</td>
<td>0.0263</td>
<td>0.9590</td>
</tr>
<tr>
<td>Image 7</td>
<td>0.0100</td>
<td>0.0251</td>
<td>0.9521</td>
</tr>
<tr>
<td>Image 8</td>
<td>0.0102</td>
<td>0.0277</td>
<td>0.9536</td>
</tr>
<tr>
<td>Image 9</td>
<td>0.0102</td>
<td>0.0280</td>
<td>0.9530</td>
</tr>
<tr>
<td>Image 10</td>
<td>0.0100</td>
<td>0.0279</td>
<td>0.9587</td>
</tr>
<tr>
<td>Image 11</td>
<td>0.0104</td>
<td>0.0285</td>
<td>0.9768</td>
</tr>
<tr>
<td>Image 12</td>
<td>0.0101</td>
<td>0.0300</td>
<td>1.0908</td>
</tr>
<tr>
<td>Image 13</td>
<td>0.0102</td>
<td>0.0313</td>
<td>0.9740</td>
</tr>
<tr>
<td>Image 14</td>
<td>0.0101</td>
<td>0.0315</td>
<td>0.9702</td>
</tr>
<tr>
<td>Image 15</td>
<td>0.0100</td>
<td>0.0274</td>
<td>0.9600</td>
</tr>
<tr>
<td>Image 16</td>
<td>0.0102</td>
<td>0.0289</td>
<td>0.9611</td>
</tr>
<tr>
<td>Image 17</td>
<td>0.0102</td>
<td>0.0270</td>
<td>0.9727</td>
</tr>
<tr>
<td>Image 18</td>
<td>0.0101</td>
<td>0.0287</td>
<td>1.0084</td>
</tr>
<tr>
<td>Image 19</td>
<td>0.0100</td>
<td>0.0255</td>
<td>1.0988</td>
</tr>
<tr>
<td>Image 20</td>
<td>0.0103</td>
<td>0.0259</td>
<td>1.0332</td>
</tr>
</tbody>
</table>

For this study, other performance criterion is the success rate of the classification of the fabric defects. To evaluate classification performances of networks, networks performance function is examined. Performance function of the designed feed forward networks is mean squared error (MSE). MSE means the average squared difference between outputs and targets. Fig. 10 shows the comparison of the targets and the outputs of the designed FFN that uses the feature vectors obtained from Fourier transform operations. Fig. 12, 14 shows the same targets and outputs comparison of the networks used for Wavelet and Gabor transforms. Fig. 11, 13, 15 shows the errors between the targets and the outputs for all transforms.
MSE of wavelet transform based approach is the smallest one (0.0346) and MSE of Fourier transform based approach is the highest one (0.0736). Plotting the network confusion matrix gives information how successful the network is in the classification (Fig. 16).

In terms of the networks classification performances, Wavelet transform based approach gave the highest success rate at 96%. Gabor transform based approach has a success rate %85. Fourier transform based approach the lowest success %80.

IV. CONCLUSION
This study was done to determine which spectral based approach for fabric defect detection is superior to the others in terms of both accuracy in classification of fabric defects and time elapsed for detection. The main criteria for performance measurement are the time lasted for the applied techinics and the success rate in the classification. Fourier Transform, Wavelet Transform and Gabor Transform were used as spectral based approaches. The experimental results show the Wavelet transform based approach in the classification for
three type defects was more efficient than the others, on other hand: Fourier transform in terms of processing time is faster than the others.

REFERENCES


[56] MATLAB-Neural Network Toolbox User Guide