Submitted to ‘IEEE Transactions on Industry Applications’

Identification of surface defects in textured materials using wavelet packets

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29 June, 2001
Abstract

This paper investigates a new approach for the detection of surface defects, in textured materials, using wavelet packets. Every inspection image is decomposed with a family of real orthonormal wavelet bases. The wavelet packet coefficients from a set of dominant frequency channels containing significant information are used for the characterization of textured images. A fixed number of shift invariant measures from the wavelet packet coefficients are computed. The magnitude and position of these shift invariant measures, in a quadtree representation, forms the feature set for a two-layer neural-net classifier. The neural-net classifier classifies these feature vectors into either of defect or defect-free classes. The experimental results suggest that the proposed scheme can be used in the automated visual inspection for the identification of surface defects.

**Key Words:** Surface Inspection, Defect Detection, Wavelet Packets, Computer Vision, Quality Assurance, Industrial Automation.
1. Introduction

Surface appearance is one of the important qualities for determining the commercial value of a product. Quality assurance in textured materials, using surface inspection, is one of the most challenging problems in machine vision. The machine vision offers accuracy, consistency, repeatability and low cost solution to the problem of subjectivity, fatigue and high cost associated with the human inspection. The gray-scale inspection images provide adequate level of information for the inspection of many textured surfaces.

The problem of surface inspection using machine vision has received considerable attention in last 20 years. The majority of prior work on the detection of surface defects has been focused on fabric texture. The existing defect detection techniques can be classified into three different categories: statistical, spectral, and model-based. The detailed description of these approaches can be found in reference [1] and only selective references are provided in this paper. Defect detection approaches based on statistical texture analysis forms the majority of work presented in the literature. However, these statistical techniques are not useful for the detection of those textured defects whose statistical features, i.e. first- and second-order moments, are significantly close from that of defect-free textured regions. High level of quality assurance requires identification of such defects, and therefore the techniques based on spectral features have been investigated in the literature [2]-[12].

Textured materials, such as woven fabric, possess strong periodicity due to the repetition of basic weaving pattern. Therefore spectral techniques using discrete Fourier transform [2]-[3], Optical Fourier transform [4], and windowed Fourier transform [5]
have been used to detect fabric defects. Escofect et al. [6] have used a bank of multiscale and multiorientation Gabor filters for the detection of local fabric defects. Ajay and Pang [7] have demonstrated yet another approach for the fabric defect detection using real Gabor functions. Jasper et al. [8] have shown that the texture information can be adapted into wavelet bases. Such an adapted wavelet bases offer high sensitivity to the abrupt changes in the surface texture caused by the defects, enabling their detection. References [9]-[12] also demonstrate several approaches for the detection of surface defects using wavelet basis functions.

1.1 Motivation and present work

The most popular multiresolution approaches, which are used for the conjoint analysis of texture features in spatial and spatial-frequency domain, are; Wigner distributions, Gabor functions, and wavelet transforms. The major drawback with the Wigner distributions is the presence of interference terms between the different components of an image [13]. Multiresolution decomposition using a bank of Gabor filters [6] results is redundant features at different scales. This is due to the nonorthogonality of Gabor functions for which they are often criticized. The multiresolution decomposition using orthogonal (or biorthogonal) and compactly supported wavelet bases can be used to avoid the correlation of features between the scales. The discrete wavelet transforms were first implemented by Mallat [14]-[15], using an octave band multilevel decomposition. This decomposition is commonly known as pyramidal-structured wavelet transform, since the different levels of image decomposition are cascaded into a pyramidal structure. Sari-Sarraf et al. [11] have shown
the usage of texture features based on pyramid-structured wavelet transform for the online web inspection.

The wavelet decomposition of an image, using pyramid-structured wavelet transform, generates a set of subimages, which contains low-frequency components of the original image. This decomposition is suitable for images in which the majority of information is concentrated in low-frequency region, \textit{i.e.} for inspection images primarily with smooth components. However, it is not suitable for textured images where the dominant frequency channels are located in the middle frequency bands \cite{16}. Many researchers have concluded \cite{16}-\cite{17} that the most significant information of texture often appears in the middle frequency bands. This is true for the real fabric images as has been suggested from the experimental results in section 3 of this paper. Hence, further decomposition in the low frequency region by conventional wavelet transform may not help much for the detection of those defects whose spectrum dominantly lies in the middle frequency region. Therefore, an appropriate way to perform wavelet decomposition of textured image (such as real fabrics) is to locate dominant frequency bands and then decompose them further. This leads to the concept of tree-structured wavelet transform or wavelet packets. This paper investigated a new approach for the inspection of surface defects using wavelet packets. The experimental results from the proposed approach, on real fabric samples, are also presented.

The organization of this paper is as follows. In section 2 a review on wavelet transform, wavelet packets, and the best-basis algorithm is presented. In section 3, the wavelet packet decomposition of some defect-free and defective fabric images is demonstrated. Section 4 describes the complete methodology of the proposed defect
detection scheme. The details of this scheme, \textit{i.e.} extraction of invariant features and their classification by neural network, are discussed in subsections following section. The experimental setup, results, and a discussion on the obtained results are presented in section 5. Finally, section 6 presents major conclusions from this paper.

2. Wavelet transform and Wavelet packets

2.1. A short review on wavelet transform

The wavelet decomposition of a signal $f(x)$ can be obtained by convolution of the signal with a family of real orthonormal basis functions $\psi_{pq}(x)$

$$\langle f(x)\psi_{pq}(x) \rangle = \int_{-\infty}^{\infty} f(x)\psi_{pq}(x)dx$$

(1)

where $p$ and $q$ are integers, and are referred to as dilation and translation parameters respectively. The basis functions $\psi_{pq}(x)$ are obtained through translation and dilation of a kernel function $\psi(x)$ known as \textit{mother wavelet} [16], \textit{i.e.}

$$\psi_{pq}(x) = 2^{-p/2}\psi(2^{-p}x-q).$$

(2)

The mother wavelet $\psi(x)$ can be constructed from a scaling function $\phi(x)$. The scaling function $\phi(x)$ satisfies the following two-scale difference equation [18]

$$\phi(x) = \sqrt{2} \sum_k h(k)\phi(2x-k)$$

(3)

where $h(k)$ is the impulse response of a discrete filter which has to meet several conditions for the set of basis wavelet functions to be orthonormal and unique. Several different sets of coefficients of $h(k)$, satisfying the required conditions, can be found in the literature and is in reference [14]-[15], [18]. The scaling function $\phi(x)$ is related to the mother wavelet $\psi(x)$ via
\[ \psi(x) = \sqrt{2} \sum_k g(k) \phi(2x-k). \] \hspace{1cm} (6)

The coefficients of the filter \( g(k) \) are conveniently extracted from filter \( h(k) \) from the following \((quadrature\ mirror)\) relation.

\[ g(k) = (-1)^k h(1-k). \] \hspace{1cm} (7)

The discrete filters \( h(k) \) and \( g(k) \) are the quadrature mirror filters (QMF), and can be used to implement a wavelet transform instead of explicitly using a wavelet function.

### 2.2 Wavelet packets

The wavelet packets introduced by Coifman and Wickerhauser [12] represents the generalization of the method of multiresolution decomposition. In pyramid-structured wavelet transform, the wavelet decomposition is recursively applied to the low frequency sub-bands to generate the next level hierarchy. The key difference between the traditional pyramid algorithm and the wavelet packet algorithm is that the recursive decomposition is no longer applied to the low frequency sub-bands. Instead, it is applied to any of the frequency bands based on some criterion, leading to quadtree structure decomposition.

The concept of wavelet packet bases has been generalized to obtain multiresolution decomposition of an image. A given function, say \( \Theta_0 \), can be used to generate a library of wavelet packet basis functions \( \{ \Theta_q \}_{q \in N} \) as follows [16]:

\[ \Theta_{2q}(x) = \sqrt{2} \sum_k h(k) \Theta_q(2x-k) \] \hspace{1cm} (8)

\[ \Theta_{2q+1}(x) = \sqrt{2} \sum_k g(k) \Theta_q(2x-k) \] \hspace{1cm} (9)

where the function \( \Theta_0 \) and \( \Theta_1 \) can be identified with the scaling function \( \phi \) and the mother wavelet \( \psi \) respectively. The equation (8) and (9) uniquely define a library of
wavelet packet bases as a set of orthonormal basis functions of the form $\Theta_q(2^l x - k)$.

Each element of the library is determined by a subset of indices $l$, $k$, and $q$, which corresponds to the scaling, dilation, and oscillation parameters respectively.

Thus a family of wavelet packets is generated by dilation, translation and modulation of a *mother wavelet*. Each of these family elements are orthonormal and same as bases similar to the sinusoid functions used in the Fourier analysis. A set of 2-D wavelet packet basis functions can be obtained from the tensor product of two separable 1-D wavelet basis functions in the horizontal and vertical directions. The corresponding 2-D filters in this set can be grouped as:

$$
\begin{align*}
& h_{LL}(k,l) = h(k)h(l), & h_{HH}(k,l) = h(k)g(l), \\
& h_{HL}(k,l) = h(k)g(l), & h_{LH}(k,l) = g(k)h(l).
\end{align*}
$$

The first and the second subscript in the equation (10) denote the lowpass and the highpass separable 1-D filters, respectively. As shown in figure 1, application of above grouped separable 2-D filters, along with subsampling by a factor of two in each of two directions, decomposes the given image into a representation having components in the four sub-bands. These four sub-bands are four sub-images that contain low frequency information (approximation $\omega_a^{2^j}$) and high-frequency details in horizontal ($\omega_h^{2^j}$), vertical ($\omega_v^{2^j}$), and diagonal ($\omega_d^{2^j}$) direction. Thus $\omega_a^{2^j}$, $\omega_h^{2^j}$, $\omega_v^{2^j}$, $\omega_d^{2^j}$ represents the decomposition results (subimages) from filters $h_{LL}(k,l), h_{HL}(k,l), h_{LH}(k,l),$ and $h_{HH}(k,l)$ respectively at scale $(j+1)$. Iterating this filtering process (figure 1) to each of the given sub-bands yields a quadtree-structure decomposition. The sub-images in the same decomposition level provide the multiple looks of the original image at different frequency bands. Figure 2 (a) shows a two-scale wavelet (pyramid-structure)
decomposition of an image. The decompositions in this figure are repeated only on low frequency subimage, i.e. $\omega_{s}^{j+1}$ or $h_{lL}$. However, for the two-scale wavelet packet decomposition shown in figure 2 (b), further decomposition is applied to all the subimages.

2.2.1 Review of the best-basis algorithm

The full wavelet packet decomposition at every scale will produce a large number of coefficients. Therefore, only the dominant frequency channels based on Shannon’s entropy criterion are used. The best basis wavelet packet tree is computed as follows [16], [19]:

(i) Decompose a given image into four subimages by convolution and decimation with a pair of QMF’s, as shown in figure 1. The given image can be viewed as parent node and subimages as the children nodes of a tree.

(ii) Compute the Shannon’s entropy ($\epsilon^{\downarrow}$) of the parent and children of this tree using equation (12).

(iii) If the sum of the entropy of four children nodes is higher than the entropy of parent node, then decomposition for this parent node is aborted.

(iv) If the sum of entropy of children nodes is lower than entropy of parent node, then the above decomposition is further applied to each of the children nodes.

The computational complexity of the wavelet packet tree grows with the level of resolution. Therefore, the best basis wavelet packet decomposition of every image at three resolution levels is used in this work. The wavelet packet coefficients from each of the sub-images are used for the feature extraction.
3. Image analysis with the wavelet packets

The wavelet packet decomposition of every acquired image using the best-basis algorithm is performed. The Daubechies minimum-support least asymmetric wavelet of filter length 4 is used in this work. Daubechies wavelets are compactly supported and are orthonormal, and are one of the most widely used wavelets. The coefficients of QMF’s, \( h(k) \) and \( g(k) \), are shown in table 1. The best-basis wavelet packet decomposition of an image sample having defect \( mispick \) (shown in figure 7 (a)) is shown in figure 3 (a). The quadtree structure of this wavelet packet decomposition, along with the node entropy values, is shown in figure 4. The pyramid-structured wavelet decomposition of this image is shown in figure 3 (b) for comparison. It can be seen that the best-basis algorithm has decomposed the vertical and the diagonal details, at the first level, further apart as there is much more information (entropy) in these frequency bands. The prior work [4] using the wavelet decomposition does not utilize this information and has only used the low frequency details (figure 3 (b)) of the images for the defect detection of local fabric defects. The amount of this information is significant, as can be observed from the node entropy values and therefore it is proposed to utilize this information for defect detection.

How much of this information is contributed from the defects? This can be observed from the three-level best-basis wavelet packet decomposition of the defect-free and the defect images. Figure 5 (a) shows the best-basis wavelet packet decomposition for the defect-free image used in this work. Similarly, the best-basis wavelet packet decomposition for the image sample with defect \( slack-end \) and \( pick-bar \) (shown in figure 7 (a) and 7 (b) respectively) is shown in figure 5 (b) and 5 (c) respectively. Comparing
the decomposition in figure 5 (a) (defect-free) with those in figure 3 (a) and figure 5 (b)-(c), it can be observed that the best-basis algorithm has not located any significant information in the horizontal and/or diagonal details (at level one) for the defect-free image, while it does for the image sample with defects. Looking into these decompositions, it is apparent that we can detect these defects as well as recognize them. But this may not be the case for those defects from which the significant information lies only in the channels corresponding to the best-basis decomposition of defect-free image. However, the information in such defects can be picked up by observing the shift in magnitude (rather than the position) of information in best-basis frequency bands. Therefore in this work not only the position of significant frequency bands but also the magnitude of the information in them is used for the detection of defects.

4. Defect identification using wavelet packet features

The block diagram of the proposed wavelet-packet based defect identification system is shown in figure 6. The best-basis wavelet packet decomposition of every image under inspection is computed, as described in section 2.2.1 and section 3.2. The dominant features from this best-basis wavelet packet tree are obtained. The extraction of these dominant features is detailed in section 4.1. These feature vectors are used to classify every inspection image into one of the two categories, i.e. with defect or without defect. The Principal Component Analysis (PCA) is used to reduce the dimension of these feature vectors, before their classification by a neural-net classifier (section 4.2). The details of this system are described in following sections.

4.1 Feature extraction
The best-basis wavelet packet decomposition of every inspection image, as described in section 2.2.1, is computed. The wavelet packet coefficient matrix for each of the terminal nodes (as shown in quadtree structure in figure 4) or channels is used to compute the texture features. Since the wavelet packet coefficients are shift-variant [20], they are not suitable for their direct use. Instead, the texture features must be shift-invariant [21]. Therefore four shift-invariant measures, from the elements of the wavelet packet coefficient matrix, are computed for each of the channels as follows:

\[
\sigma^i = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} \left( \omega^i(m,n) - \mu^i \right)^2, \quad \text{where} \quad \mu^i = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} \omega^i(m,n) \quad (11)
\]

\[
\varepsilon^i = -\sum_{m=1}^{M} \sum_{n=1}^{N} \left( \left( \omega^i(m,n) \right)^2 \log \left( \left( \omega^i(m,n) \right)^2 \right) \right) \quad (12)
\]

\[
\alpha^i = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} \frac{\left( \omega^i(m,n) - \mu^i \right)^4}{(\sigma^i)^4} \quad (13)
\]

\[
\beta^i = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} \frac{\left( \omega^i(m,n) - \mu^i \right)^5}{(\sigma^i)^5} \quad (14)
\]

where \( \omega^i(m,n) \) denotes an element of the best-basis wavelet packet coefficient matrix in each \((i^{th})\) channel, i.e. terminal nodes of best-basis wavelet packet tree, \( M \) and \( N \) represent the vertical and the horizontal size of matrix \( \omega \). The \( \mu^i \) is the mean of the matrix elements in each channel \((i)\). Using equations (11)-(14), four features for every best-basis wavelet packet coefficient matrix, i.e. standard deviation \( \sigma^i \), entropy \( \varepsilon^i \), third moment or kurtosis \( \alpha^i \), and the fourth moment or skewness \( \beta^i \), are computed. Thus each of the channels is now represented by four features, i.e. \( \sigma^i, \varepsilon^i, \alpha^i, \beta^i \). In this work, only five (ad-hoc) dominant values of each of these features, among all of the channels or the terminal nodes of quadtree decomposition (e.g. figure 4), are used. As investigated in the previous section, not only the magnitude of the features but also their location on the
quadtree decomposition is important. Therefore, the five dominant values of each of the four features, i.e. $\sigma^i$, $\varepsilon^i$, $\alpha^i$, $\beta^i$, along with their location (node number, an integer value) on the best-basis wavelet packet tree are used. Thus in the present work, these ten values for each of the four features form a feature vector of dimension $40 \times 1$ for the characterization of every image.

4.2 Feature Classification

Classification of large dimension feature vectors generates computational and overfitting problems for the neural-networks. Therefore the dimension of the feature vectors is reduced such that the reduced feature vector ($v_m$) accounts for as much of variations in the original vector ($u_n$). This is achieved by a linear orthogonal transformation $\Lambda$, which transforms each of the $n$-dimensional vectors into $m$-dimensional uncorrelated vectors such that $n \geq m$.

$$v_m = \Lambda^T u_n', \text{ where } u_n' = u_n - E[u_n]$$ \hspace{1cm} (15)

‘$E$’ denotes the expectation operator, $u_n$ and $v_m$ are the vectors of dimension $n \times 1$ and $m \times 1$, respectively. As detailed in reference [22]-[23], the $n \times m$ transformation matrix $\Lambda$ can be obtained from the Singular Value Decomposition of feature vector matrix $U'$. The matrix $U'$ can be formed from a set of zero mean feature vectors $u'_n$, each of which constitutes the column of matrix $U'$. The linear dimension reduction technique, briefly discussed in this section, is known as Karhaunen-Loeve (KL) transform or Principal Component Analysis (PCA), and is discussed with greater details in [22]-[23]. In this work, the PCA is used to reduce the dimension of $40 \times 1$ the feature vectors by neglecting 2 % of the total variance in the transformed feature space. The reduced set of feature
vectors is used to classify the inspection image using a two layer feed-forward neural network.

The architecture of a feed-forward neural network (FFN) can be described by

\[ \Theta^p_i = \sum_{j=1}^{N_{p-1}} w_{ji}^{p-1,p} o_j^{p-1}, \quad o_i^p = \tanh(\Theta^p_i) \quad \text{for} \quad p = 1, 2. \]  

(16)

where \( w_{ji}^{p-1,p} \) represents the weights connecting \( j^{th} \) neuron at \( (p-1)^{th} \) layer to the \( i^{th} \) neuron at \( p^{th} \) layer, \( \Theta^p_i \) represents the sum of weighted inputs applied to \( i^{th} \) \( \left( i = 1, \ldots, N_p \right) \) neuron in \( p^{th} \) layer, and \( o_i^p \) is the output from the \( i^{th} \) neuron in \( p^{th} \) layer. The two layer FFN employed hyperbolic tangent sigmoid activation function since its output is in the range \(-1\) to \(1\). The target output value of \(1\) for defect-free images (feature vector) and \(-1\) for images with defect was given to network during training. The network was trained to minimize sum of squares error function

\[ E = \frac{1}{2} \sum_{k=1}^{K} (o_k - t_k)^2 \]  

(17)

where \( K \) is the total number of input-output pairs in the training set, \( o_k \) is the output of the network for \( k^{th} \) pair of training set, and \( t_k \) is the \( k^{th} \) target value. The connection weights \( w_{ji} \) are updated after presentation of every feature vector, using Levenberg-Marquardt [24] algorithm.

The two-layer FFN with 20 input nodes and one output node was employed in this work to classify feature vectors in one of the two classes, \( i.e. \) defect-free or with defect. This FFN was trained for the maximum of 1000 steps with the learning rate of 0.01. The training was aborted if the maximum performance gradient of \(1e-10\) is achieved. While training FFN, the problem related to the existence of local minima during the
computations of weights and biases are very frequent. Therefore there is no guarantee that the achieved training error is global. In this work, the FFN was trained 10 times [25] with the same parameters and the results with smallest of training errors of all the results are reported.

5. Experimental setup and results

Several real fabric samples were gathered from textile loom and divided into two classes; (i) defect-free and (ii) those having defects. Images of these fabric samples were acquired under backlighting and covered 1.28 × 1.28 inch² area of fabric. These images were digitized into 256 × 256 pixels, with eight-bit of resolution (256 gray-levels). While selecting the images for the proposed experiment, we preferred those images (defect) in which the defects were hidden in defect-free texture, and therefore defect identification was expected to be difficult. Figure 7 shows eight different categories of fabric defects used in this experiment. The 40 × 1 feature vectors for each of the images used in this experiment were computed, as detailed in section 4.1. As described in section 4.2, dimensions of these feature vectors are reduced by using PCA. It was found that the dimension of every feature vector is reduced to 12 × 1 from 40 × 1, when those features which contributed to less than 2 % of the total variance in the transformed feature space are neglected. Each of these 12 × 1 feature vectors are classified using two-layer FFN as described in section 4.2.

In this experiment, a total of 42 images having defect and equal number of defect-free images are used for training, and 16 images are used for testing. Each of these 42 training images (16 for testing) was composed of one of the eight different categories of fabric defects shown in figure 7. The 42 images (with defect) used for training were
composed of; seven images (due to availability of two extra images) from the category in figure 7 (a) and five images from remaining seven category. Two images from each of the eight categories are used for testing. The training curve for the two-layer neural network used in this experiment is shown in figure 8.

The classification rate of this trained neural network was tested from the training and testing images. All of the training images produced the expected scores at the output, i.e. \( \leq 0 \) for the images with defects and \( > 0 \) for the defect-free images. Therefore, the classification rate for the training images was found to be 100 %. The scores of the neural network output from the testing images are summarized in table 2. The first column in this table contains the identifier for the eight different categories of defects shown in figure 7. The results in this table show that the 12 fabric samples with defect, out of total 16 used for testing, has been successfully detected (75%). Similarly, 11 defect-free fabric samples, out of total 16 used for testing, have been successfully classified (68.75 %) as defect-free. Thus an overall classification rate of 71.86 % has been achieved.

5.1 Discussion

The experimental results presented above are promising and demonstrate potential application of wavelet packets in the identification of surface defects. In this study, for the reasons of computational simplicity, the maximum level of best-basis wavelet packet decomposition was fixed to three. The performance (classification rate) achieved in this study can be improved by increasing the level of the wavelet packet decomposition. It has been shown in reference [21] that the higher levels of decompositions perform better than the lower levels, for the classification of textured images. For every inspection image used in this experiment (Figure 7), the defects form a
fraction of defect-free texture in the image. However, the average of features [equation (11)-(14)] from the complete image, i.e. defect and defect-free portion, has been assumed to be belonging to defect while training FFN. Therefore, due to this averaging effect, the reliability of features from defect images is low. The classification results can be improved by increasing this reliability, i.e. by using small size images such that a large portion of these images comprises defect. However, the computational time is critical for the real-time inspection and this will significantly increase when the small size images are used to inspect the entire width of the web. The level of wavelet packet decomposition (three) and the size of images ($256 \times 256$ pixels), chosen for the evaluation of the proposed approach, offer a tradeoff between the performance and computational complexity. The small number of training and testing images does not generate a reliable measure of performance. Therefore a large number of training and testing images are desirable. The small number (due to limited availability) of training and testing images used in this experiment have shown promising results, but a further improvement, with the increase in number of training images, is expected. The wavelet packet decomposition generates orthogonal bases quite similar to those obtained with the Karhunen-Loève (KL) transform. However, as discussed in reference [15], the computing cost of the wavelet packet decomposition is much less than that of KL transform, and is hence more attractive for real-time inspection.

6. Conclusions

This paper has investigated a new approach for the detection of fabric defects using wavelet packets. Prior work on fabric defect detection [4], using wavelet decomposition (pyramidal), only utilizes the information in the lower-frequency bands. However the
best-basis wavelet packet analysis in section 3.2 has suggested that the occurrence of the fabric defects (e.g. mispick, slack-end) provides new information in the higher-order frequency bands, i.e. horizontal, vertical and diagonal details. This information can be vital for the detection of those fabric defects, which cannot be detected by the approach in prior work [11] using the information from the lower-frequency bands. The defect detection results for some of the fabric defects with very subtle intensity variations, e.g. in figure 7 (a) and 7 (g), were excellent (100 % detection). However, the overall classification rate (71.86 %) is not high, mainly due to the false alarm (31.5 %) generated from the defect-free images. The experimental results presented in this paper offer a tradeoff between the computational complexity and the performance. However, better results can be obtained by the measures suggested in section 5.1 of this paper. Although the experimental results in this paper are demonstrated only from the real fabric samples, but the proposed approach can be potentially used for the detection of surface defects in other textured materials, i.e. paper, wood, or steel-rolls.
References


Table 1: Coefficients of the Daubechies wavelet transform filter used in the experiments.

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<th>h(0)</th>
<th>g(0)</th>
<th>g(0)</th>
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<td>0.71484657</td>
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<td>g(1)</td>
<td>g(1)</td>
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<td>-0.03288301</td>
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<tr>
<td>h(7)</td>
<td>g(7)</td>
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Table 2: Scores of the neural network output from the experiment.

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<th>S.No.- Category</th>
<th>Class 1</th>
<th>Class 2</th>
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<td>Samples with-defect</td>
<td>Samples without-defect</td>
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<td>-1.0060</td>
<td>1.0060</td>
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<tr>
<td>2.a</td>
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Classification rate for the test images (from the above data) = 71.86 %
Classification rate for the training images = 100 %
Figure 1: Multiresolution decomposition of an image using QMF.

Figure 2: Two-scale (a) wavelet and, (b) wavelet packet decomposition using QMF filters.
Figure 3: Three-scale (a) best-basis wavelet packet and (b) wavelet decomposition of the fabric defect *mispick* shown in figure 7 (a).

Figure 4: Quadtree representation of the best-basis wavelet packet decomposition shown in the figure 3 (a).
Figure 5: Best-basis wavelet packet decomposition for (a) defect-free image, (b) image sample with defect *slack-end* (shown in figure 7 (b)) and, (c) image sample with defect *pick-bar* (shown in figure 7 (c)).

Figure 6: Block diagram of a wavelet packet based defect detection system.
Figure 7: Fabric samples with eight different categories of defects used in the experiment.

Figure 8: Training curve for the neural network used as the classifier.