Abstract.
This paper presents a feature extraction algorithm using wavelet decomposed images of an image and its complementary image for texture classification. The features are constructed from the different combination of sub-band images. These features offer a better discriminating strategy for texture classification and enhance the classification rate. In our study we have used the Euclidean distance measure and the minimum distance classifier to classify the texture. The experimental results demonstrate the efficiency of the proposed algorithm.

Keywords: Wavelet decomposition, Texture, Feature Extraction, Classification.

1. Introduction
Texture classification is very important in image analysis. This process plays an important role in many machine vision applications such as biomedical image processing, automated visual inspection, content based image retrieval, and remote sensing applications. To design an effective algorithm for texture classification, it is essential to find a set of texture features with good discriminating power. Most of the textural features are generally obtained from the application of a local operator, statistical analysis, or measurement in a transformed domain. Generally, the features are estimated from co-occurrence matrices, Law’s texture energy measures, Fourier transform domain, Markov random field models, local linear transforms etc. A number of texture classification techniques have been reported in literature [1, 2, 3, 9]. The wavelet methods [1, 9, 15] offer computational advantages over other methods for texture classification and segmentation.

Initially, texture analysis was based on the first order or second order statistics of textures. The co-occurrence matrix features were first proposed by Haralick [11]. Weszka [7] compared texture feature extraction schemes based on the Fourier power spectrum, second order gray level statistics, the co-occurrence statistics and gray level run length statistics. The co-occurrence features were found to be the best of these features. This fact is demonstrated in a study by Conners and Harlow[12], In[13], Haralick features are obtained from wavelet decomposed image yielding improved classification rates. Hiremath and Shivashankar[6] have considered Haralick features for texture classification using wavelet packet decomposition.

In Montiel et al[5], texture features are characterized by considering intensity and contextual information obtained from binary images. The conditional co-occurrence histograms are computed from the intensity and binary images. To obtain binary images the fixed thresholds have been used.

A wavelet transform-based texture classification algorithm has several important characteristics: (1) The wavelet transform is able to decorrelate the data and achieve the same goal as the linear transformation used in[4]. (2) The wavelet transform provides orientation sensitive information which is essential in texture analysis. (3) The computational complexity is significantly reduced by considering the wavelet decomposition.

It is evident that the context or the position information of a pixel in an image is very important for the purpose of classification. In this paper, we propose a novel wavelet based feature extraction algorithm for texture classification problem. The features are extracted from the cumulative histograms generated using the different combinations of approximation and detail subbands of the wavelet decomposed image. Further, complementary image is used for enhancing white or gray details embedded in dark regions [10]. The features so obtained have more uncorrelated texture information. The features obtained from the proposed algorithm have better discriminating strategy for texture classification.

The paper is organized as follows: In the section 2, the wavelet decomposition process is discussed. The proposed feature extraction algorithm is presented in section 3. The texture training and classification are explained in section 4. In section 5, experimental results of the proposed method are discussed in detail. Finally, section 6 concludes the discussion.
2. Wavelet decomposition of an image

The continuous wavelet transform of a 1-D signal \( f(x) \) is defined as
\[
(W_a f)(b) = \int f(x) \Psi_{a,b}^* (x) dx
\]  
(1)
where the wavelet \( \Psi_{a,b} \) is computed from the mother wavelet \( \Psi \) by translation and dilation,
\[
\Psi_{a,b} (x) = \frac{1}{\sqrt{|a|}} \Psi \left( \frac{x-a}{b} \right)
\]  
(2)

Under some mild assumptions, the mother wavelet \( \Psi \) satisfies the constraint of having zero mean. Eq. (1) can be discretized by restraining \( a \) and \( b \) to a discrete lattice \( (a = 2^b, b \in \ell) \). Typically it is imposed that the transform should be non-redundant, complete and constitutes a multiresolution representation of the original signal. The extension to the 2-D case is usually performed by using a product of 1-D filters. In practice, the transform is computed by applying a separable filter bank to the image:
\[
\begin{align*}
A & = [L_x] \ast [L_y] \ast I_{1,2} \\
H & = [L_x] \ast [G_y] \ast I_{1,2} \\
V & = [G_x] \ast [L_y] \ast I_{1,2} \\
D & = [G_x] \ast [G_y] \ast I_{1,2}
\end{align*}
\]  
(3)
where * denotes the convolution operator, \( \downarrow 2, \downarrow 1 \) \( \downarrow 1,2 \) denotes the downsampling along the rows (columns) and I is the original image, L and G are lowpass and highpass filters, respectively. A is obtained by lowpass filtering and is referred to as the low resolution image at scale one. H, V, D are obtained by bandpass filtering in a specific direction and thus contain directional detail information at scale one. The original image I is thus represented by a set of sub images at several scales. Every detail subimage contains information of a specific scale and orientation. Spatial information is retained within the subimage.

Wavelets are functions generated from one single function \( \psi \) by dilations and translations. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different levels, where each level is further decomposed with a resolution adapted to that level.

The sub-bands labeled H, V and D correspond to Horizontal, Vertical and Diagonal coefficients respectively, representing the detail images, while the sub-band A corresponds to coefficients representing the approximation image. The values of transformed coefficients in approximation and detail images are essential features, which are useful for texture classification and segmentation. In other words, the features derived from these approximation and detail coefficients uniquely characterize a texture.

3. Proposed feature extraction algorithm:

1. Consider the image \( X \) and its complementary image \( X' \).
2. Apply DWT on \( X \) using Haar wavelet which gives the approximation(A) co-efficient and the detail co-efficients: horizontal(H), vertical(V) and diagonal(D).
3. Consider the pair of images (A,H) for feature extraction. For a pixel \( x \) in A and corresponding pixel \( y \) in H, their 8-nearest neighbours are as shown in Fig. 2

4. Construct two histograms \( H_1 \) and \( H_2 \) for A based on the maxmin composition rule:
   Let \( \alpha = \max(\min(x_h), \min(y,a_i)) \)
   Then, \( x \in H_1 \), if \( \alpha = \min(x_h) \)
   and, \( x \in H_2 \), if \( \alpha = \min(y,a_i) \)
   It yields 16 histograms, 2 for each direction \( i = 1,2,..,8 \).
5. Construct the cumulative histogram for each histogram obtained in step(4) and normalize it. The points on the cumulative frequency curve are the sample points.
6. From the sample points of each cumulative histogram obtained in step (5), calculate the following features:
   i. Slope of the regression line fitted across the sample points.
   ii. Mean of the sample points.
   iii. Mean deviation of the sample points.
7. Repeat steps 3-6 for the pair of images (A,V), (A,D), (A,abs(V-H-D)) for feature extraction.
8. Repeat steps 2-7 for the complementary image \( X' \).

The above process generates 384 features (2 (images) x 4 (combinations) x 3 (features) x 16 (histograms)) which constitute the feature vector \( f \). The vector \( f \) is used for texture classification (Table 1: feature Set). If the image size is \( n \times n \) and \( m \) nearest neighbours are considered, the complexity of the above algorithm is \( O(m n^3) \).

Also, during experimentation, the above algorithm is repeated by considering different combinations (Table 1; Feature sets F1, F2 and F4) in step 7.

4. Texture training and classification

Each texture image is subdivided into 16 equal sized blocks out of which 8 randomly chosen blocks are used as samples for training and remaining blocks are used as test samples for that texture class.
### 4.1 Training

In the texture training phase, the texture features are extracted from the 8 samples selected randomly belonging to each texture class, using the proposed feature extraction algorithm. The average of these features for each texture class is stored in the feature library, which is further used for texture classification.

### 4.2 Classification

In the texture classification phase, the texture features are extracted from the test sample $x$ using the proposed feature extraction algorithm, and then compared with the corresponding feature values of all the texture classes $k$ stored in the feature library using the distance vector formula,

$$D(k) = \sqrt{\frac{1}{N} \sum_{j=0}^{N} [f_j(x) - f_j(k)]^2} \quad (4)$$

where, $N$ is the number of features in $f$, $f_j(x)$ represents the $j^{th}$ texture feature of the test sample $x$, while $f_j(k)$ represents the $j^{th}$ feature of $k^{th}$ texture class in the library. Then, the test texture is classified as $k^{th}$ texture, if the distance $D(k)$ is minimum among all the texture classes available in the library.

### 5. Experimental results

#### 5.1 Experimental data

In order to assess the discrimination capability of wavelet based feature sets, we have performed experimental tests using the same data presented in [8]. The test defines 32 test categories from selected images of Brodatz (1966) [4] collection as shown in the Fig. 2. For the 32-category problem, texture samples are obtained from a 256x256 image with 256 gray levels. Each image is subdivided into 16 blocks of 64x64 pixels and each block is transformed into a new block by 90$^\circ$ rotation. This produced 1024 blocks. Half of the data is selected randomly choosing 8 blocks and the corresponding transformed blocks. This data is used to define classes and the remaining blocks to evaluate the classification process.

#### 5.2 Computation of features

The features are computed for each texture block separately by considering 3x3 neighborhoods. For comparative analysis, texture classification is done using four different feature databases constructed by using the different combinations of wavelet decomposed images:

- **F1**: $(A,H), (A,V), (A,D)$
- **F2**: $(A,H), (A,V), (A,D), (A,\text{abs}(V-H-D))$
- **F3**: $(A,H), (A,V), (A,D), (A,\text{abs}(V-H-D))$
- **F4**: $(A,H), (A,V), (A,D), (A,\text{abs}(D-H-V))$

The features extracted from joint occurrence of the pixels of approximation and detail coefficients have more uncorrelated texture information.

#### 5.3 Classification results

From Table 1, it is found that when classification is carried out with F3, the mean success rate is maximum (96.13) as compared to F1, F2, F4 and the method proposed by Montiel et al. [5]. The proposed method is simple and computationally less expensive than the method in [5], which employs computationally expensive genetic algorithm. The improved performance of the proposed algorithm can be attributed to the co-occurrence features extracted from the wavelet decomposition of the image and its complement, in which the detail subbands contain discriminating information. The difference image of detail subband images also contains discriminating information which enhances the classification performance.

#### Table 1. Average classification accuracies(%) over 10 experiments for 32 texture category

<table>
<thead>
<tr>
<th>Sl.No.</th>
<th>Texture</th>
<th>Montiel et al. (2005)</th>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
<th>Proposed</th>
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<td>Bark</td>
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<tr>
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<td>93.75</td>
<td>93.75</td>
<td>93.75</td>
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<tr>
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<td>100.00</td>
<td>100.00</td>
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<tr>
<td>4</td>
<td>Burlap</td>
<td>100.00</td>
<td>98.75</td>
<td>98.75</td>
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<td>98.75</td>
<td>98.75</td>
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<tr>
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<td>93.75</td>
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<td>D4</td>
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<tr>
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<tr>
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<td>97.50</td>
<td>100.00</td>
<td>98.75</td>
<td>100.00</td>
<td>100.00</td>
</tr>
</tbody>
</table>

- **Fig. 3:** Texture images from Brodatz album. The image Nos 1 to 32 correspond to the texture Sl.No. 1 to 32 in Table 1.
6. Conclusion

We have proposed a feature extraction algorithm using wavelet decomposed images of an images and its complementary image for texture classification. The characterization defines the features constructed from the different combination of sub-band images. Experimental results show the combination of detail subbands with approximation subband helps to improve the classification rate at reduced computational cost. Further, these texture features can be used for efficient segmentation.

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