# CLASSIFICATION OF TEXTURES IN SAR IMAGES USING MULTI-CHANNEL MULTI-RESOLUTION FILTERS

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## ABSTRACT

*The paper presents texture classification using multi-channel filters: Gabor filters and discrete wavelet transform. We have used a bank of 8 Gabor filters 2 wavelet filters: Daubeschies and Haar, for analyzing and classifying the textures in SAR images. The parameters of the Gabor filter bank are obtained using the energy measure of the response to the filters. The Fuzzy C-means classifier has been used for unsupervised segmentation. A combination of Gabor and wavelet features provides better performance.*

## 1. INTRODUCTION

Texture plays an important role in low-level image analysis and understanding. There is no formal or unique definition of texture, making texture analysis a difficult and challenging problem. Nevertheless, most of the real world images are considered to be made up of distinct textures. Texture segmentation deals with identification of regions where distinct textures exist, so that further analysis can be done on the respective texture regions alone.

Classification and segmentation of texture content in digital images has received considerable attention during the past decades and numerous approaches have been presented. Statistical, model-based, and signal processing techniques are the most commonly used approaches. A common denominator for most signal processing approaches is that the textured image is submitted to a linear transform, filter, or filter bank, followed by some energy measure.

The focus of this paper will be on multi-rate and multi-resolution signal processing approaches applied for classification of texture in SAR images. The test images were generated from SAR images by suitably selecting region templates with homogeneous texture. Two filtering-based texture feature extraction schemes have been presented. The focus will be on filtering, keeping the other components same.

## 2. BRIEF REVIEW OF TEXTURE SEGMENTATION

Most methods of texture segmentation, for the identification of different texture surfaces, are based on wavelet features, MRF models, STFT features, co-occurrence matrices, and geometric shape of texels and PCA analysis. A few papers are discussed in the following, which deal with the segmentation of textures using wavelet transform and Gabor filters.

A comparative study of various types of filters (heuristically designed and optimized filter banks) for texture classification, which includes, Gabor dyadic filters, wavelet transforms, DCT, AR models, co-occurrence matrices and eigenfilters, is presented by Randon and Hüsoy [1]. They compare the filters, using classification errors and computational complexity as the performance criteria. One important result is that wavelets performed better than Gabor filters, in general. Comparisons of the pyramidal and tree-structured wavelets with the Gabor filtering approaches was presented by Pichler et. al.[2]. Results show that both the wavelet-based methods are sub-optimal for feature extraction purpose, because the center frequency, orientation and bandwidth cannot be selected. The paper also concludes that Gabor filtering outperforms the wavelet cases but is computationally more expensive.

Methods of texture segmentation based on discrete wavelet transform have been widely used. A method based on a hierarchical wavelet decomposition technique is introduced by Salari and Ling [3], where he uses the Daubechies 4-tap filters to decompose the original image into three detail and one approximate sub-band images followed by a K-means clustering for segmentation. Results are shown on a few regular and homogeneous real-world textures. Charalampidis and Kasparis [4] use a set of new roughness features for texture segmentation and classification. Wavelets are used to extract single-scale and multiple-scale texture roughness features. These are then transformed to a rotational invariant feature vector, which has the information of texture direction. Iterative K-means algorithm has been used for segmentation and Baye's classifier for classification. Results are shown using a large set of real world texture images. Lu et. al. [5] proposed a method of unsupervised texture description using wavelet transform. The proposed methodology has four stages. The first stage computes a smoothed local energy of the wavelet coefficients in high-frequency bands, as features for segmentation. The second stage performs a coarse segmentation using a multi-thresholding technique. In the third stage, the features at different orientations and scales are fused in intra-scale and inter-scale respectively. In the last stage, ambiguously labeled pixels are reclassified in a fine segmentation technique. Segmentation results at various scales are integrated by inter-scale fusion to determine the number of classes. Results are shown on a few real-world images, with the use of various types of wavelet filters.

Dunn et. al. [6] presents an algorithm to design Gabor filters specially tuned to segment images with bipartite textures. The parameter tuning of the set of Gabor filter bank is the key contribution of this approach. Results are shown mostly on simulated and a few real world samples.

The methodology presented in this paper uses a combined representation of texture classification, based on Gabor and wavelet features. This representation combines the discriminability of these multi-rate, multi-resolution filters to provide improved segmentation results.

## 3. METHODOLOGY OF SEGMENTATION

Figure 1 shows the steps of the overall methodology for texture classification. The filtering stage consists of dyadic discrete wavelet transforms and a bank of Gabor filters. The input image i*(x, y)* is comprised of disjoint regions of N textures $t_1, t_2 \ldots t_N$ with $N \geq 2$. This input is applied to *k* filter channels, where each channel consists of a bandpass Gabor function $h_j(x, y)$. The filtered output $ih_j(x, y)$ *is* the convolution of the input image with Gabor filter given by:

$$ih_j(x, y) = h_j(x, y) ** i(x, y)$$

where ** denotes convolution in 2-D. Figure 2(a) and (b) show two typical examples of Gabor filters with different parameters. The 2-D Wavelet transform uses a family of wavelet functions and its associated scaling function to decompose the original image into different channels, namely the *low-low*, *low-high*, *high-low* and *high-high* (*A, V, H, D* respectively) channels. Figure 3(a), (b) show the 2-channel level-1 dyadic decomposition of an image. The LP and HP *filters* are used to implement the wavelet transform. The size of the individual subimages in each channel in this case is half as that of the original image. The Gabor and DWT filter coefficients are then post-processed using a set of non-linear functions, which compute the local energy estimates (as shown in Figure 1). These non-linear functions consist of two stages:

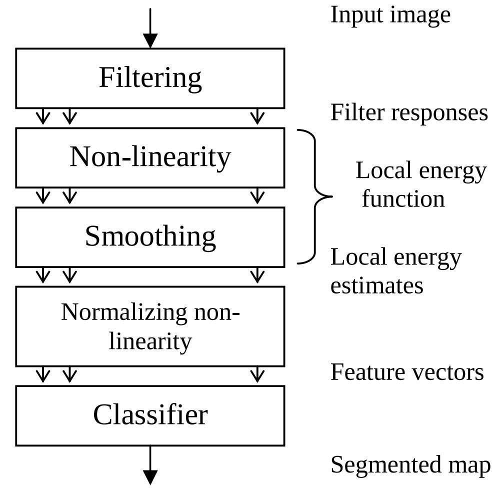



Figure 1: Stages of processing for texture classification.

(i) Subtracting the local mean and obtaining the mean subtracted magnitude of the filter output as:

$$m_j(x, y) = \left| ih_j(x, y) - \mu_j(x, y) \right|$$

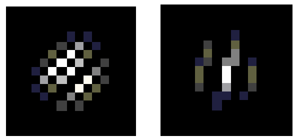
where $ih_j(x,y)$ is the $j^{th}$ channel output of the filter and $\mu_j(x,y)$ is the local mean image of the filter output

(ii) Smoothing by a large Gaussian function i.e. a lowpass Gaussian post-filter $g_p(x, y)$ is applied to each $m_j(x, y)$ yielding post-filtered energy of the $j^{th}$ filter channel as:

$$e_j(x, y) = m_j(x, y) ** g_p(x, y)$$

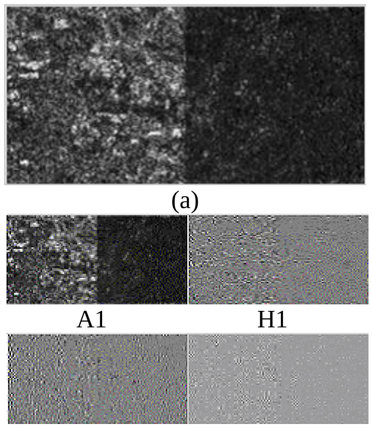
The feature vectors computed from the local energy measure estimates are local mean $\mu[e_j(x, y)]$ and local variance $\sigma[e_j(x, y)]$, which represent local texture characteristics. These feature vectors are computed from the various filtered images and provided to the classifier to segment the texture patterns in the image. At the classifier stage both supervised and unsupervised segmentation could have been done. Since this is an initial exploratory study, we have decided to use the fuzzy c- means clustering (FCM) algorithm.

In the process of combining the Gabor and DWT features for giving input to the FCM classifier, we had to ensure that the dimensionality and resolution of the feature vectors were compatible. We have used 8 different Gabor filters and 2 types of wavelet transforms. Daubechies 8-tap and Haar together gave 8 features for every pixel, which ensured equal weightage for both the filtering techniques. To ensure resolution compatibility, the wavelet features were upsampled to the same size as that of the Gabor. Results of the FCM classifier using the features of both the filters are described in the next section.



(a) (b)

Figure 2: Real part of Gabor Filter at different scales (σ) and orientations (θ): (a) σ=2, θ=45°, ω=7 (b) σ=2, θ=76°, ω=4.




(b)

Figure 3: (a) Sample SAR texture image (b) Its DWT level-1 coefficients using the Daubechies 8-tap filter.

## .4. RESULTS WITH SAR IMAGES

We now illustrate the performance of the feature extraction methods using several examples of texture images. The SAR images were closely observed to find the different textures that existed in the image. These texture regions where cropped to form 4-5 distinct textures per SAR image. This consumed the basis textures in our data set. These textures were paired up to form bipartite texture images in our database. The DWT was computed using the two most commonly used filters viz. Daubechies and Haar with level-1 decomposition only. The Gaussian width used for post-filtering was chosen to be 1.5 times the width of the window used for feature extraction. Eight different Gabor filters were selected based on a trial and error method. We observed the energy responses with varying parameter values and the ones that provided contrasting signatures for at least 2-3 different regions were chosen. This set of eight filters for the Gabor filter bank is not optimal, but we avoided specific tuning which could lead to a supervised approach. The parameters of the eight Gabor filters are given in Table I. The width of the Gaussian filter in this case was twice that used for computing the local mean. To ensure unbiased comparison, the segmentation algorithm was kept the same. The feature vector for Gabor filter based classification had a set of 16 features, while the wavelet based technique had 8 each. The textures cropped from the SAR images were combined to form two-texture images and four-texture images. Table II shows the results of texture classification on these images. Column (a) in Table II shows the input texture images. Corresponding outputs of the FCM classifier are shown in the columns of Table II with different features obtained using: (b) Daubechies, (c) Haar, (d) Gabor, and (e) combined features of Gabor, Haar and Daubechies filters.

## 5. CONCLUSIONS

A combination of features from two different types of multi-resolution and multi-channel filters, in general provides superior classification of texture images. A combination of Gabor and wavelet features may be sufficient for segmentation over a wide variety of SAR textures. The method combines the advantages (or feature discriminability) of both these filters to provide an improved performance. One can also follow [6], [8] to determine an optimal set of parameters for the Gabor filter to obtain better results. Experimentation using SVM and ANN for supervised segmentation of SAR images using similar features is currently under investigation.

| **Filter(i)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
|---|---|---|---|---|---|---|---|---|
| $\boldsymbol{\sigma_{1i}}$ | 2 | 2 | 1 | 2 | 2 | 3 | 1 | 2 |
| $\boldsymbol{u_i}$ | 5 | 1 | 5 | 3 | 2.7 | 2 | 4 | 6 |
| $\boldsymbol{v_i}$ | 5 | 4 | 5 | 1 | 2.7 | -1 | 4 | -3 |

Table I: Gabor filter parameters $(\sigma_{1i}, u_i, v_i)$ of the 8 filters in the bank

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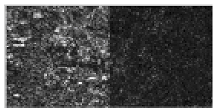
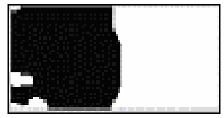
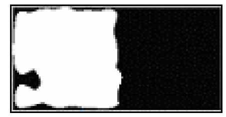
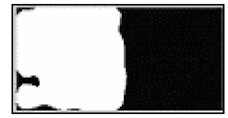
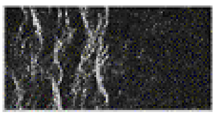
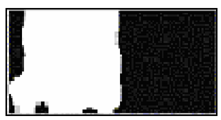
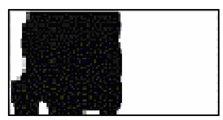
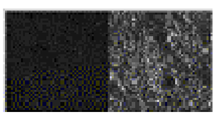
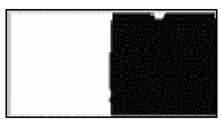
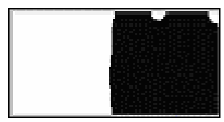
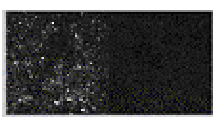
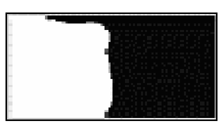
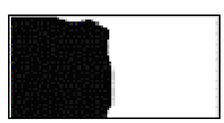
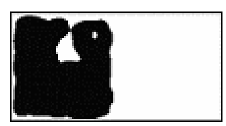
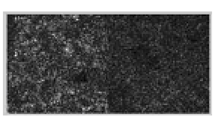
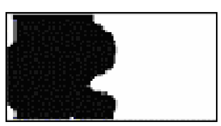
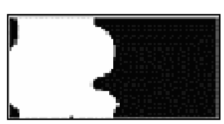
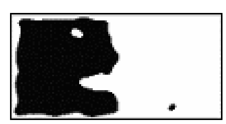
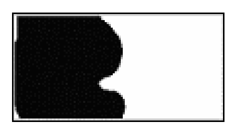
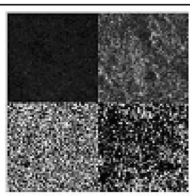
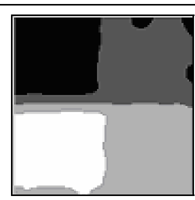
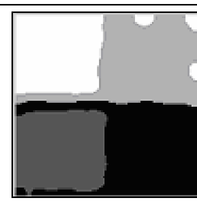
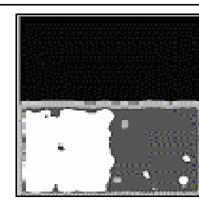
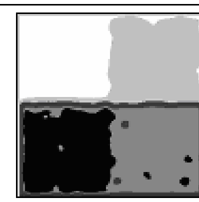
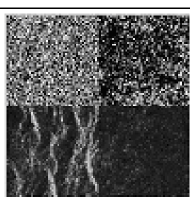
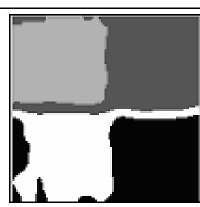
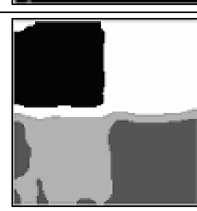
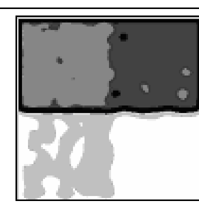
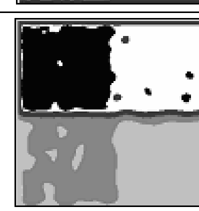
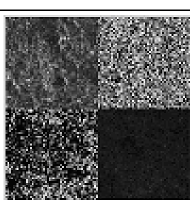
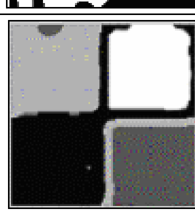
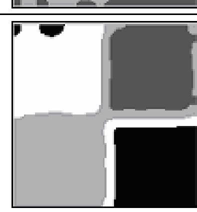
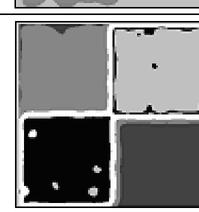
| (a) Input Image | Results of classification | | | |
|---|---|---|---|---|
| | (b) Daubechies | (c) Haar | (d) Gabor | (e) Combined features |
| 1  |  |  |  |  |
| 2  |  |  |  |  |
| 3  |  |  |  |  |
| 4  |  |  |  |  |
| 5  |  |  |  |  |
| 6  |  |  |  |  |
| 7  |  |  |  |  |
| 8  |  |  |  |  |

Table II: Experimental results of classification of textures: (a) Input images. Segmented image with features obtained using (b) Gabor filter only (c) Daubechies filter only (d) Haar transform only and (e) Combined features from Gabor, Daubechies and Haar filters.