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Research Article

Transform-Based Texture Feature Extraction Techniques

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ABSTRACT

Feature extraction in image processing is used for extracting certain features of interest such as edge, shape, and texture features. These features are necessary to classify the image into major classes such as water body, urban, vegetation, and others. This analysis is done on synthetic aperture radar (SAR) image. The image is acquired from Sentinel-1A satellite. In this paper, the performances of two feature extraction techniques are analyzed with respect to classification. Image analysis is limited by the inherent noise present in SAR images, known as speckle. Pre-processing is necessary to remove the speckle noise. For this purpose, Lee filter is applied on the image. For feature extraction, many spectral-based methods are used. Among them, Laws mask and Gabor filter-based feature extraction techniques are discussed in this paper. Laws mask, a bank of filters, that is appropriate for texture identification. Among the 25 masks, level mask, spot mask, ripple mask, edge mask, and wave mask are implemented here. Gabor filter is a linear filter used to represent and to discriminate texture features. The extracted features are grouped into different classes using classification techniques. The *k*-means and fuzzy *c*-means (FCM) clustering are the two unsupervised classification techniques discussed here. The Gabor filter provides better feature information compared to Laws mask. FCM is preferred over k-means clustering since it provides good results with both Laws mask and Gabor Features. The experimental result shows that the Gabor filter with FCM provides high accuracy of 74%.

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INTRODUCTION

Feature extraction is a method used in image processing as a segmentation step.[1] Feature extraction is done after pre-processing.[2] In this process, the image is converted into features which give information about the image.[3] Features contain some information to distinguish between classes.[4] The features may be a spatial feature, a histogram feature, a transform feature, an edge and boundary feature, a shape feature, a color feature, or a texture feature. Using laws mask and Gabor filter, texture features are extracted.[5] The features extracted from different methods are then converted into feature vectors and then used for further processing.[6] In this paper, the feature vectors are then classified so that the image can be classified into four major classes such as water body, Urban, vegetation, and others. It is easier for the classifier to classify the image using the features since classes can be easily distinguished from feature extraction step.[7] In this paper, the main focus is on feature extraction. However, classification is essential to classify the land into four major classes. Many approaches have been used till now to extract features. Here, two spectral-based methods are discussed, and the performance of these methods is analyzed, and then, the results are shown in the upcoming sections.

Study area and dataset

Synthetic-aperture radar (SAR) is a coherent side-looking radar system which generates high-resolution remote-sensing imagery. SAR is a form of radar that is used to create two or three dimensional images of objects such as landscapes. SAR uses the motion of the radar antenna over a target region to provide finer spatial resolution than conventional beam-scanning radars.[8] SAR images have wide applications in remote sensing and mapping of the surfaces of both the earth and other planets.[9] Good range resolution relies principally upon the properties of the transmitted waveform. SAR operates in four modes as follows: Strip-map mode, interferometric wide (IW) swath mode, extra-wide swath mode, and wave mode.[10]

For undergoing the survey, the range covered over the region is 8 km. The SAR image is obtained from the Sentinel-1A, a European radar imaging satellite. Sentinel-1 is a two-satellite constellation with the prime objectives of land and ocean monitoring. The satellite carries a C-band SAR which will provide images in all light and weather conditions. Sentinel-1 operates in C-band. The satellite frequency is 12–18 GHz (ku band). The Sentinel-1A was launched on April 3, 2014. The instrument used in this satellite is SAR-C. Sentinel-1 satellite is about 693 km above the earth surface. It covers up to 400 km. It is a Sun-synchronous satellite. The incident angle is 20–45°. Transmitting frequency is 5.8–6.4 GHz and the receiving frequency is 3.6–4.2 GHz. The mode used for capturing this image is IW Swath mode. The swath width is 250 km. The polarization is VV and VH.

Some of the applications for launching Sentinel-1A satellite are as follows: (a) Monitoring sea ice zones, the arctic environment, and surveillance of marine environment; (b) monitoring land surface motion risks; (c) mapping of land surfaces such as follows: Forest, water, and soil; and (d) mapping in support of humanitarian aid in crisis situations. Figure 1 depicts the SAR image, taken on July 2016 with the spatial resolution of 20 m * 22 m.

In the next section (Section II), the methodology of the proposed work was illustrated. It explains in detail in the following: (1) The pre-processing of the data before being used for evaluation, (2) the feature extraction methods to be applied, such as laws mask and Gabor filter, and finally, (3) the classification methodology to be used for the evaluation of two cases. In Section III, experimental results using the Sentinel-1A SAR image of the site are demonstrated. Finally, some concluding remarks are given in Section IV.

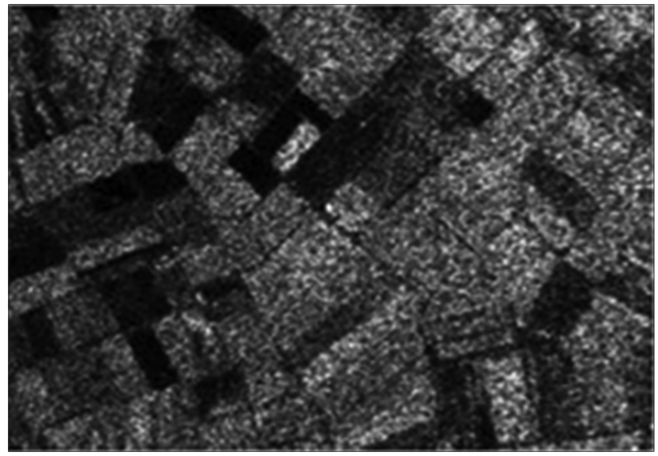

Figure 1: Synthetic-aperture radar image

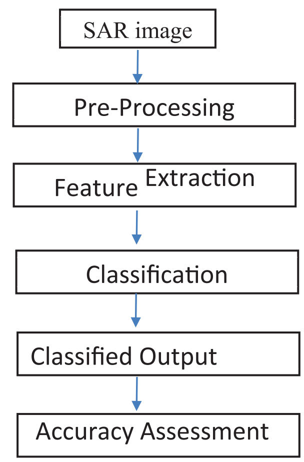

Figure 2: Methodology of the proposed work

PROPOSED METHODOLOGY

The general approach outlined here is to extract the features from an image so that it is easy for classification. Figure 2 shows the basic block diagram of the proposed work. It involves three main steps as follows: Pre-processing, feature extraction, and classification.

Every block of the proposed work is necessary to be implemented to obtain the classified output.

Pre-processing

Pre-processing is essential to improve the visual interpretability.[11] In this step, the image is enhanced by removing noise. Radar image appears noisier than an optical image. SAR image is highly affected by speckle noise.[12] Speckle noise occurs due to the coherent summation of the signals scattered from ground scatterers distributed randomly within each pixel. Speckle is a granular noise that inherently exists in and degrades the quality of the active radar, synthetic-aperture radar,[13] medical ultrasound, and optical coherence tomography images. In order to reduce speckle in SAR images, some adaptive speckle filters, namely, Gamma, Lee, frost, enhanced Lee (EL), and enhanced frost (EF) filters are used. Among these, Lee filter calculation produces an output value close to the original input value in higher contrast regions and a value close to the local mean for uniform areas.[3] In uniform areas, more smoothening occurs. The Lee filter follows the below equation,

$$Img\ (i,j) = Im + W * (Cp - Im) \tag{1}$$

where, Img is the pixel value after filtering

I_m is the mean intensity of filter window C_p is the center pixel

W is the filter window

Figure 3 depicts the speckle noise removal using Lee filter. The pre-processed image contains more information compared to the input image in Figure 1.

Feature extraction

Feature extraction can be carried out using statistical, structural, and spectral-based methods. Among them, spectral-based feature extraction methods are applied in the proposed work. Since spectral methods analyze the frequency content of an image, it gives more spectral information of an image.[14] The two methods such as Laws mask and Gabor filters are used.

Laws mask

Laws mask is an approach for texture identification using filtering. Derived from the concept of texture energy defined at each pixel after a series of particular convolution with selected mask, laws mask can produce the texture energy measurement for the analysis of the texture property of each pixel.[5] Among the 25 filters, the most commonly used masks are level mask, edge mask, spot mask, wave mask, and ripple mask.

Level mask identifies any variations in a homogeneous region of the image to which it is convolved with, whereas convolving with edge mask, the edges or abrupt changes in the input image can be extracted. Convolution of spot mask identifies any point level changes in the input image. Ripple mask extracts any surface texture roughness in the given imagery. Moreover, the convolution with wave mask extracts any periodic variations in the image.

Figure 4 demonstrates the features extracted using laws mask. Each feature gives unique information. While classifying the image, each feature has to be converted to feature vector.

Gabor filter

A Gabor function is a sinusoidal signal with a given frequency and orientation, modulated by a Gaussian function.[15] The filter used here is called Gabor filter. The Gabor filter bank is defined by its parameters including frequencies, orientations, and smoothing parameters of the Gaussian envelope.[16] The Gabor filter is obtained by using different scales and orientations. A complex 2-D Gabor filter over the image domain (x, y) is defined as follows,

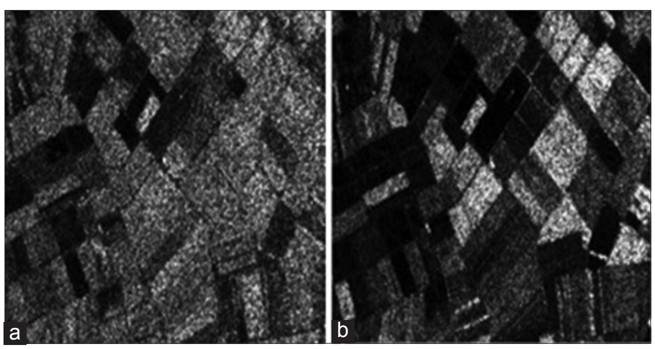

Figure 3: (a) Original image, (b) pre-processed image

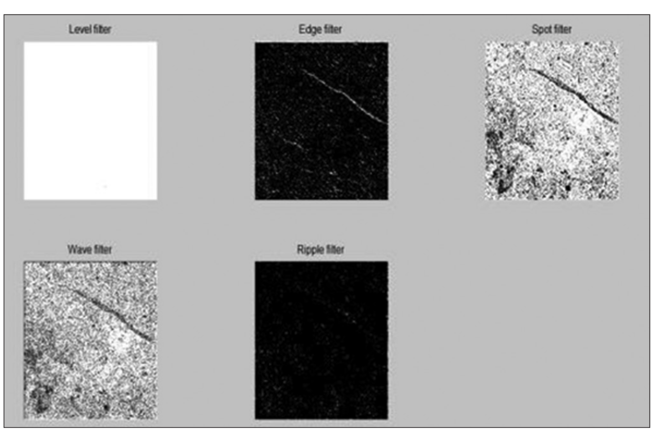

Figure 4: Features extracted using laws mask

$$f(x,y,\omega,\theta,\sigma_x,\sigma_y)=\frac{-1}{2\pi\sigma_x\sigma_y}\exp\left[\frac{-1}{2}\left(\left(\frac{x}{\sigma_x}\right)^2+\left(\frac{y}{\sigma_y}\right)^2\right)+j\omega(x\cos\theta+y\sin\theta)\right] \quad (2)$$

where, σ is the spatial spread

$\omega = 2\pi f$, f is the radial frequency

θ is the orientation

If a set of Gabor filters with different orientations and frequencies are used, then a host of features can be extracted.[17] Totally, 32 filters are obtained for four scales and eight orientations.

Gabor filter can achieve the best localization performance both in time and frequency domain through analyzing the uncertainty of signal in direction and spatial frequency.[18]

CLASSIFICATION

Image classification is a significant tool for digital image analysis and object recognition. The major steps involved in image classification are determination of suitable classification system, selection of training and testing samples, and the classification technique.[19]

k-means clustering

k-means algorithm is a well-known clustering algorithm popularly known as Hard *c*-means algorithm. It is an algorithm to classify or to group the objects based on attributes/features into *k* number of group. *k* is positive integer number.[6] The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid.

k-means clustering aims to partition "*n*"	Observations
Into "*k*" clusters in which each observation	Belongs to

The cluster with the nearest mean, serving as a prototype of the cluster.[20] This algorithm splits the given image into different clusters of pixels in the feature space, each of them defined by its center. Initially, each pixel in the image is allocated to the nearest cluster. Then, the new centers are computed with the new clusters.

Fuzzy c-means Clustering (FCM)

Blue, green, and yellow respectively. Figure 9 depicts the classification result of laws mask feature.

Fuzzy clustering is a soft clustering. In soft clustering, data elements can belong to more than one cluster and a membership level associated with each element indicates the strength of that element with a particular cluster.[11] In this algorithm, membership levels are assigned to each pixel, and then, it is used to assign data elements to clusters.

Main objective of fuzzy c-means algorithm is to minimize,

$$J(U,V)=\sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{ij})^m\,||x_i-v_j||^2 \quad (3)$$

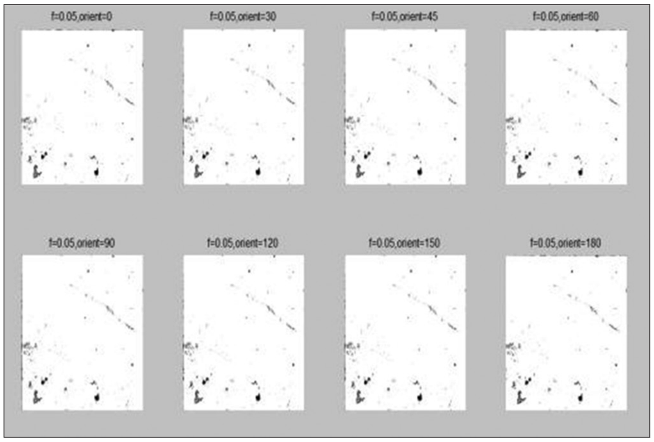

Figure 5: Features extracted for scale f=0.05

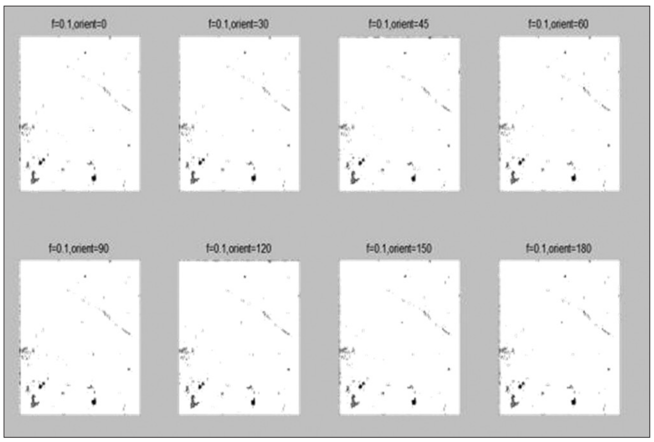

Figure 6: Features extracted for scale f=0.1

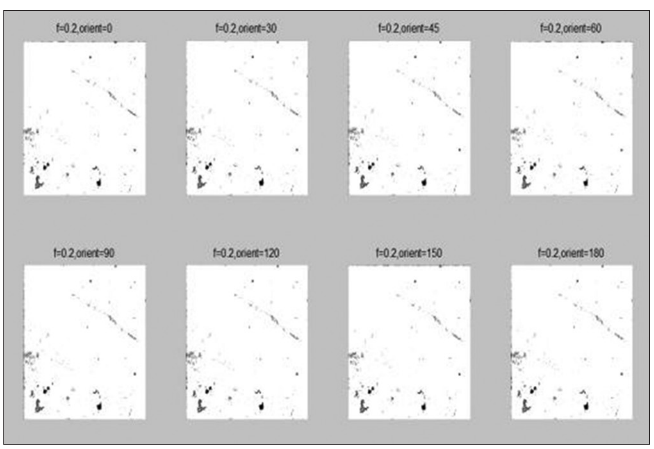

Figure 7: Features extracted for scale f=0.2

Classification approaches can be implemented to classify the total scene content into a limited number of major classes.[7] Figure 10 depicts the classification result of Gabor feature.

Let X = {x_1, x_2, x_3., x_n} be the set of data points and V = {v_1, v_2, v_3., v_c} be the set of centers.

- Randomly select *"c"* cluster centers.
- Calculate the fuzzy membership "μ_{ij}" using:

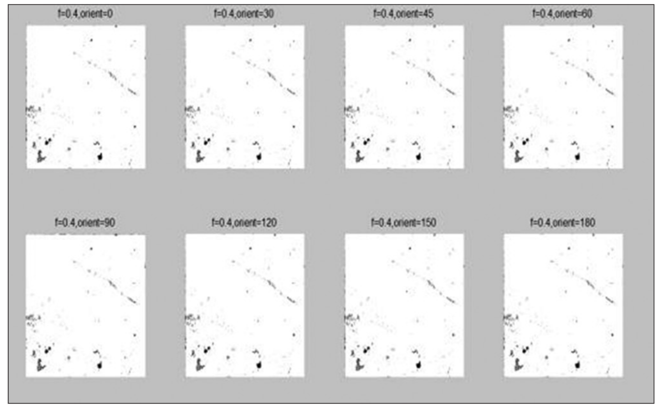

Figure 8: Features extracted for scale f=0.4

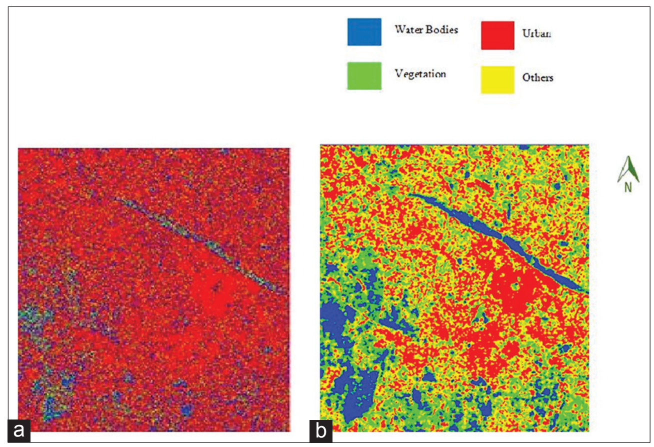

Figure 9: *k*-means classification for (a) laws mask feature. (b) Gabor feature

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \tag{4}$$

- Compute the fuzzy centers "v_j" using:

$$v_j \frac{\sum_{i=1}^{n} (\mu_{ij})^m x_i}{\sum_{i=1}^{n} (\mu_{ij})^m}, \forall j = 1, 2, \ldots c \tag{5}$$

- Repeat the steps until the minimum "*J*" value is achieved or $||U^{k+1} - U^k|| < \beta$

EXPERIMENTAL RESULTS

Classification approaches can be implemented to distinguish one or more specific classes of terrain (such as water bodies, paved surfaces, irrigated agriculture, forest cutting, or other types of disturbances) within the landscape. The two unsupervised classification techniques used in this paper are *k*-means and FCM. In the classification, the land Cover is classified into four classes as urban, water body, Vegetation, and others and represented by red.

Figure 10 shows fuzzy *c*-means classification for (a) laws mask feature and (b) Gabor feature.

Accuracy assessment

A classification is not complete until its accuracy is assessed.[8] Construction of confusion matrix or error matrix is a best way to assess the accuracy of a classification. An accuracy table usually provides the performance result of a classification in terms of overall accuracy, producer accuracy, and user accuracy. The performance evaluation is done by calculating the accuracy using the confusion matrix and is tabulated. The classified images are assessed for the accuracy by comparing with the Google Earth ground truth. Optimal classified outputs are only taken for the accuracy assessment by computing confusion matrix. Totally, 100 sample points are taken, and the accuracy is calculated. (Table1-4).

User accuracy is a measure of the reliability of an output map generated from a classification scheme. Producer accuracy is a measure of the accuracy of a particular classification scheme. Overall accuracy is the percentage of correctly classified pixels.

Diagonals represent sites classified correctly according to reference data, and off-diagonals represent misclassified pixels. Overall accuracy is the percentage of correctly classified pixels.

CONCLUSION

Classification is done on the basis of extracted feature vectors into four classes, namely, water bodies, vegetation,

Table 1: Laws mask and *k*-means

Classes	W	U	V	Others	Row total	X (%)	Y (%)
W	16	11	7	9	43	37.21	80.0
U	4	12	2	5	22	54.54	48.0
V	1	0	13	2	16	81.25	54.17
Others	0	2	2	15	19	78.94	50
Column total	20	25	24	30	100		

Overall accuracy=56%, W: Water body, U: Urban, V: Vegetation, X: User accuracy, Y: Producer accuracy

Table 2: Laws mask and FCM

Classes	W	U	V	Others	Row total	X (%)	Y (%)
W	14	4	1	6	25	56.0	73.68
U	1	20	2	3	26	76.92	50
V	2	2	13	1	18	72.22	68.42
Others	2	14	3	12	31	38.70	54.54
Column total	19	40	19	22	100		

Overall accuracy=59%, W: Water body, U: Urban, V: Vegetation, X: User accuracy, Y: Producer accuracy

Table 3: Gabor filter and *k*-means

Classes	W	U	V	Others	Row total	X (%)	Y (%)
W	18	3	0	1	22	81.81	58.06
U	2	20	2	0	24	83.33	66.67
V	5	3	19	2	29	65.51	86.36
Others	6	4	1	14	25	56	82.35
Column total	31	30	22	17	100		

Overall accuracy=71%, W: Water body, U: Urban, V: Vegetation, X: User accuracy, Y: Producer accuracy

Table 4: Gabor filter and FCM

Classes	W	U	V	Others	Row total	X (%)	Y (%)
W	17	4	3	2	26	65.38	68.0
U	3	20	1	4	28	71.43	76.92
V	4	0	21	2	27	77.78	84.0
Others	1	2	0	16	19	84.21	66.67
Column total	25	26	25	24	100		

Overall accuracy=74%, W: Water body, U: Urban, V: Vegetation, X: User accuracy, Y: Producer accuracy

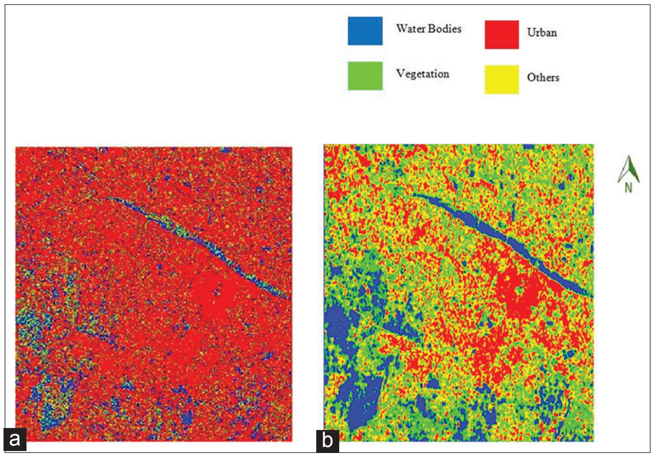

Figure 10: Fuzzy *c*-means classification for (a) laws mask feature (b) for Gabor feature

urban, and others. The classified images are assessed for the accuracy by comparing with the Google Earth ground truth. Optimal classified outputs are only taken for the accuracy assessment by computing confusion matrix. The feature vectors obtained using the two techniques are fed independently to the two classification mechanisms. Thus, four different results are obtained. On analyzing the results using the accuracy assessment table, the following conclusions are made. The Gabor filter provides better feature information compared to the laws mask. FCM has robust characteristics for ambiguity, and it can retain more information than *k*-means clustering.[17] It gives the best result for overlapped dataset and comparatively better than *k*-means algorithm. Hence, Gabor filter with FCM produces higher accuracy (74%) compared to other methods.

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