A Study of the Invariance Properties of Textural Features in SAR Images

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Abstract In this paper, we compare the performance of a number of different texture features for SAR image analysis. These features are derived from the gray-level co-occurrence matrix, local statistics, and lognormal random field models. The features are compared based on: (i) their invariance or robustness with respect to natural changes in SAR signatures; and (ii) their discrimination ability and classification accuracy. The invariance of the texture features is investigated on a set of 13 ERS-1 SAR images of the same scene, captured under different conditions. Two main conclusions can be drawn from this study: (i) the texture features are not invariant with respect to natural changes in the mean backscatter values; and (ii) texture fusion and selection by combining texture features obtained by different models significantly improve the classification accuracy.

INTRODUCTION

The SAR backscatter signature of an area depends on certain weather conditions. If an area is imaged several times, factors like the soil moisture content and the temperature may cause large variations in the resulting backscatter values. These variations depend on the ground-cover class of the area, as different cover types are affected by different scattering mechanisms. Thus, calibration of the images will not remove these class-dependent signature variations.

For an image classification task, the most important feature is normally the tonal information represented by the backscatter values. However, as the mean backscatter value of an area changes, it has been proposed that texture can be an important additional feature for classification purposes. Although no precise definition of texture exists, certain concepts of texture can be defined [9]. Texture involves the spatial distribution of gray levels in a local region. It contains important information about the structural arrangement of surfaces and their relationship to their neighboring surfaces. Some studies [1, 6] have indicated that classification based on texture might be more robust than classification based on gray values alone. Based on these initial results, it is important to study multiple SAR images of the same scene carefully to investigate the reliability of the texture features. In this paper, we investigate the invariance properties of several popular texture extraction methods for SAR images taken under different weather conditions. We also compare the discrimination ability of different texture features and apply feature selection to select the optimal subset of features on several images. Feature selection has previously been applied in small-scale studies for texture analysis of SAR imagery [4, 5].

The texture extraction methods included in this study are the following: features derived from the gray-level co-occurrence matrix [3], features computed from first-order statistics, and features estimated from modelling the SAR images with a multiplicative autoregressive model [2].

TEST DATA

A set of thirteen ERS-1 SAR images of Kjeller, Norway taken during the fall of 1991 was used to study the invariance of the textural features to the observed natural changes in backscatter values. These images were taken from the same position on the path of the satellite, thus no co-registration of the images were necessary. Fig. 1 shows a small part of the scene for some of the images.

Five general ground cover classes were considered: urban areas, water, forests, and two types of agricultural areas: unplowed and plowed fields. Large variations in SAR signature for the same ground-cover class were observed with different wind conditions (for water areas), temperature, and soil moisture (for forest and agricultural areas). Information about temperature, precipitation, and soil moisture was available for each acquisition date, and this was compared to the observed signature changes.

TEXTURE FEATURES

A very brief description of the texture models used is given below. For land-use classification in Norway, the average size of typical regions is rather small. Thus, we need to limit the window size used in the texture computations. A window of size 9×9 pixels will be used.

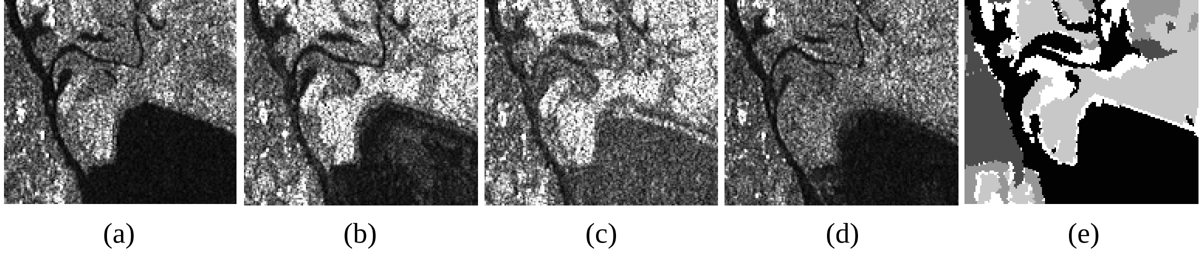

Figure 1: *ERS-1 SAR images from October 23 (a), November 25 (b) and 28 (c) , and December 7 (d) , 1991 of Kjeller, Norway are shown. The SAR signature changes are due to wind conditions (water areas), and soil moisture content and temperature (forest and agricultural areas). A general ground cover map is included for reference purposes (e).*

Features based on co-occurrence matrices

Co-occurrence features are based on gray-tone spatial dependencies [3]. They are computed from a co-occurrence matrix of relative frequencies of gray levels at neighboring pixels (separated by distance d and angle θ). We used $d = 1$ and computed an average for $\theta = 0^o, 45^o, 90^o$, and 135^o. The following features were included in the study [3]: *angular second moment, contrast, entropy, cluster shade, inertia,* and *inverse difference moment.*

Features from local statistics

Based on local statistics, the following features are computed: *Power-to-mean ratio*, $PMR = \sigma/\mu$, where σ is the local standard deviation and μ is the local mean of the backscatter values, *Skewness*, $SKW = \frac{E[(f(x,y)-\mu)^3]}{\sigma^3}$, *Kurtosis*, $KUR = \frac{E[(f(x,y)-\mu)^4]}{\sigma^4}$, *Contrast* [7], and *Homogeneity* [7].

Features from lognormal field models

Following Frankot and Chellappa [2], we model the SAR image using a multiplicative autoregressive random field (MAR). The parameters of the model will be used as texture descriptors. Let the observed image $f(x,y)$ be represented by a white-noise-driven multiplicative system, where $g(x,y) = \ln f(x,y)$ follows a Gaussian autoregressive (AR) model (see [2, 8] for details). We used the least squares estimates for the parameters.

INVARIANCE OF TEXTURE FEATURES

Invariance studies were performed for all the texture features. Each feature was computed for each SAR image, and the invariance was evaluated by comparing the within-class variations between the images to the between-class variations for each image.

The speckle noise present in SAR images is multiplicative in the sense that the backscatter standard deviation is proportional to the mean backscatter value. When the weather conditions cause an increase in the local mean backscatter value, the corresponding standard deviation will also increase. An effect of this is that the co-occurrence matrix will show an increase in the off-diagonal values, and a smaller number of elements in the matrix will have close-to-zero values. By inspecting the definitions of the GLCM features, we can predict the changes in feature values when the mean backscatter value increases: (i) *Angular Second Moment* and *Inverse Difference Moment* are measures of homogeneity. An increase in the mean backscatter value should lead to a decrease of the ASM and IDM values. (ii) *Entropy, Inertia, Contrast,* and *Cluster Shade* are measures of contrast and should increase with an increase in the mean backscatter value.

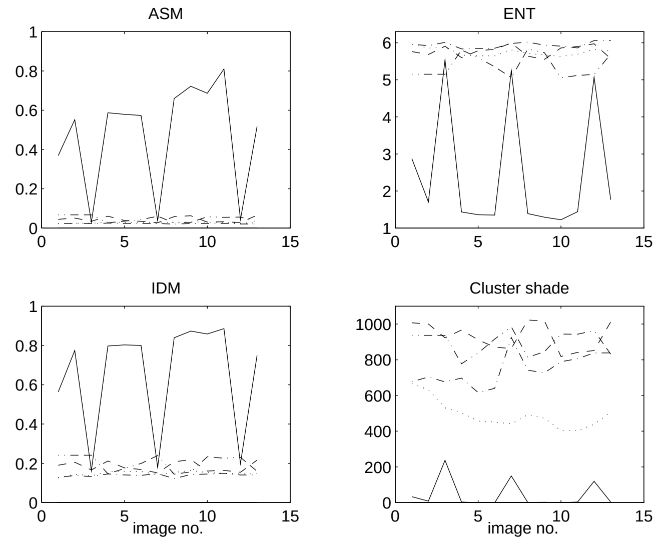

Figure 2: *Average values for the GLCM features for the 13 SAR images for the five ground-cover types. Water, —— ; Urban areas, - - -; Forest, ...; Unplowed agricultural areas, -.-.-; Plowed agricultural areas, ..- - .*

Fig. 2 shows plots of the mean values for each of the five classes for the 13 images for the four GLCM features: ASM, IDM, Entropy, and Cluster Shade. The predicted effects of an increase in the mean backscatter value can easily be observed for the water class by comparing, e.g., the feature values for image nos. 2 and 3. The average values for each of these features shows large variations with varying mean backscatter values. The texture features do not show better invariance properties than the average backscatter value.

The corresponding invariance plots for features from local statistics and lognormal field models showed that none of the texture features were invariant to natural changes in backscatter values. Some of the features were found to be very unstable (in the sense that their values showed large variations, and these variations were not correlated with the weather conditions). Other features behaved in a predictable manner when the average backscatter value changed.

The multiplicative speckle noise can, in principle, be transformed into an additive noise by applying a logarithmic transform to the images. To check whether this could lead to a better invariance of the texture features, we computed the features from logarithmically transformed images. The resulting features did not show better invariance properties.

TEXTURE CLASSIFICATION

The classification performance of the different approaches to texture computation were compared for several images. The classification accuracies were computed using a quadratic classifier and the leave-one-out method for error estimation. On an average, the error rate was 25.8% for classification based on lognormal-field features, compared to 31.5% for GLCM features, and 43.0% for features from local statistics. The classification accuracy based on a speckle-reduced backscatter image, with no texture features, was 33.0% on an average. In all the experiments, the features derived from the lognormal field model performed significantly better than the other texture models.

We also applied feature selection using Whitney's method [10] to the pooled set of all the texture features available to select the subset of features with the best discrimination ability. Fusion of the texture features reduced the average classification error rate from 25.8% using only the lognormal features to 18.8% using the selected subset of features. Reasonably consistent results were found when applying feature selection to different images.

CONCLUSIONS

In this study, we have investigated the invariance properties of texture features based on the co-occurrence matrix, features based on local statistics, and features based on a lognormal field model to check if the texture features could be used in an operational monitoring system. None of the texture features tested were found to be invariant to natural changes in the SAR signature. To use texture features as part of a monitoring system, we suggest establishing a library of texture signatures taken under different conditions, and then choosing the appropriate database entry for classification.

The classification accuracies using different texture models were compared. The lognormal random field model consistently produced the best results. Texture fusion and selection by combining texture features obtained by different models further improved the classification accuracy significantly.

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