Classification of Urban Areas in multi-date ERS-1 images using Structural Features and a Neural Network

Wilhelm Hagg, Karl Segl, Manfred Sties
Institute for Photogrammetry and Remote Sensing
University of Karlsruhe, Englerstr. 7, D-76128 Karlsruhe
Phone: +49 721 608 4131, Fax: +49 721 694 568 Email: hagg@ipf.bau-verm.uni-karlsruhe.de

Abstract — In this paper we describe a new method to extract structural informations from images. The loss of spatial resolution and distortions from edges, as it occurs with standard texture algorithms, are reduced to a minimum. Furthermore, we describe the inhomogeneity by three different structure types according to the structures contained in SAR images. Finally we use a Neural Network (RBF-Network) to get a more precise classification of urban areas from SAR-images.

Keywords: urban areas, structural features, texture, spatial resolution, edge insensibility, neural networks, RBF networks

INTRODUCTION

The supervised classification of multi-date ERS-1 images using smoothed grey level images usually causes a considerably high degree of misclassification within urban areas. This is due to the similarity of the spectral signatures of urban areas and some agricultural areas as well as the resemblance of the signatures of forest areas and loosely populated areas. To reduce the degree of misclassification, additional information is needed. In the past, this task was often solved by computing texture features from the image. A main problem of texture features is their sensibility to edges between homogeneous planes. In addition, the extension of the measurement area results in a loss of geometric resolution within the image.

The sensitivity of texture features relative to edges may be reduced, if the planes defined by the edges are not too small. This may be done by limiting the measurement area to a sub-area around each pixel, where the corresponding quantity has its minimum. Thus we avoid calculating the quantity from an area containing an edge. In this manner two features are extracted in order to describe the "presence" and the "intensity" of inhomogeneity, two more features to describe the "kind of inhomogeneity", i.e. the structure it results from.

There are mainly three different kinds of structures within SAR images, which may be characterized by the spatial distribution of the dynamic peaks, namely 1) an uniform spatial distribution, 2) an accumulation along an edge and 3) a random spatial distribution caused by single scattering targets. The first addresses areas of high standard deviation without visible structures, the second represents small, but not necessarily homogeneous planes as they occur in agricultural areas with small fields, and the third one describes the phenomenon of urban areas as imaged by SAR sensors, i.e. randomly arranged corner reflectors. Two more features are needed to determine the kind of inhomogeneity, the first case of an uniform spatial distribution is covered by the absence of the other ones.

Since the extracted features mostly show a complex distribution in the feature-space (they may even be constant for some training areas), it is unfavourable to use them in a Maximum-Likelihood classification. One promising alternative to handle such problems very well are Neural Networks. Therefore a Radial-Basis-Function (RBF) network was developed and implemented, which is generated automatically from the training data. This RBF network was successfully applied to the extracted features.

EDGE INSENSITIVE MEASUREMENTS

The extraction of structural features within a square window around each pixel will result in distortions caused by edges and in a loss of spatial resolution. On the other hand it is necessary to extend the measurement area as much as possible to achieve reliable results and not just noise from textural features. Therefore, we limit the measurement area to a sub-area around each pixel where the corresponding quantity has its minimum; thus, edges regarding to the quantity measured are ignored. In practice, we found a good compromise between loss of spatial resolution and maximum sized measurement area by dividing the square around the pixel in four sub-squares by a horizontal and a vertical line. All extracted features described in the remainder of this paper are derived from the image in that manner. In addition, there is a problem when edges are close together of such a kind, that the size of the respective planes is approximately the same or less than the measurement area. This problem will be addressed by two of the extracted structural features below.

INHOMOGENEITY IN SAR IMAGES

In SAR images the presence of speckle noise complicates the estimation of inhomogeneity caused by objects on the earth's surface. The most simple measurement—the standard deviation σ—leads to different results for homogeneous areas at different mean values μ, since the speckle noise is of multiplicative nature. Therefore, we need to calculate the "relative standard deviation"

$$RSD = \frac{\sigma}{\mu} \qquad (1)$$

as a measure of inhomogeneity, which is independent from the mean grey level in SAR images.

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In the presence of small structures consisting of homogeneous planes we will mistakenly find inhomogeneity with this feature. In order to avoid misclassification we use another quantity: the maximum size of a homogeneous plane found around each pixel, where the plane may be one of eight triangles around the pixel. We derive this value from the EPOS speckle filter ([1]) where a homogeneous plane is need to calculate the mean in order to reduce standard deviation. The criterion used in the speckle filter is also the relative standard deviation. This second feature, the "Size of Homogeneous Area" (SHA) is not redundant. It is a measure for the statement "this pixel contains inhomogeneity", while the RSD is a measure for the degree of the inhomogeneity.

DESCRIBING STRUCTURES

Once we have detected inhomogeneity it would be useful to describe the structure it is caused by. This may be done by different texture features as it for example Haralick ([2]) did. These measurements allow the description of a lot of different patterns, including ordered and disordered textures. For remotely sensed data with a ground resolution of about 25 meters, as in the case of ERS-1 or Landsat-TM, this approach is not very suitable, because there are only some simple textures distinguishable. In addition, distortions from edges decrease the overall accuracy of a classification. Since most of the patterns we found in ERS-1 SAR-images are irregular we call them structures instead of textures. We found mainly the following patterns in inhomogeneous areas:

Noise Pattern with an uniform spatial distribution of dynamic peaks

Small Planes with an accumulation of dynamic peaks at the edges, and

heaps of single scattering peaks with a random spatial distribution of dynamic peaks.

In order to extract features adapted to SAR images we try to describe these patterns by different measurements. For a distinction we need two features describing the inhomogeneity by edges and by single scattering peaks. The noise pattern is then detected by the absence of the others.

Identification of Small Planes

The identification of small planes may be done by a measurement within the frequency spectrum of the image. Only structures containing planes at different grey levels will have portions at low frequencies (except zero). To avoid the expense of calculating a Fourier transform we apply a simple low pass filter to the image by averaging four values within a square window and interpret the standard deviation as a measure of the frequency spectrum amplitudes within the according band. The standard deviation σ of the original image represents the amplitudes of all frequencies, the standard deviation σ_{low} of the low pass filtered image represents those of the low frequencies. Averaging is done within the sub-window around each pixel where the standard deviation has its minimum, in order to preserve edges. The "low frequencies portion" (LFP) may then be approximated by the fraction

$$LFP = \frac{\sigma_{low}}{\sigma}. \tag{2}$$

If we assume the pixels within the measurement area to be independent samples of the same event (i.e. the same ground coverage and uncorrelated pixels), averaging of N values will reduce the standard deviation within the area by a factor $1/\sqrt{N}$. If there are different events the standard deviation will be reduced less than the given factor and hence we may detect small planes within the structure by analyzing the relation given by the LFP above. The correlation of neighbouring pixels does not matter, because we need no absolute measurement of the amount, the standard deviation will be reduced.

Notice that the extracted feature is independent of the local standard deviation, if no structure is present. It is determined just by the structural property of the area and of course, by a constant obtained from the correlation of neighbouring pixels. Therefore, its information is different from the "Size of Homogeneous Area" described above in order to detect small planes of homogeneous areas.

Identification of Single Scattering Peaks

Urban areas in SAR images are typically characterized by randomly distributed scattering peaks. Therefore, a measurement to identify such structures has to ignore the spatial distribution and just evaluate the local histogram. Typically, the histogram consists of a Gaussian distributed majority and some outliers at higher grey levels caused by corner reflectors. To characterize such histograms we use the number of outliers and the amount of grey levels they differ from the majority distribution. To ensure independence from the local standard deviation we use the proportion of the outliers at the top and the bottom of the histogram to characterize the "Local Distribution Asymmetry" (LDA):

$$LDA = \frac{\sum\limits_{\substack{i=1 \\ x_i > \mu + f\sigma}}^{N} x_i - \mu}{\sum\limits_{\substack{i=1 \\ x_i < \mu - f\sigma}}^{N} \mu - x_i} \tag{3}$$

. To limit the measurement to the outliers the sum contains only pixels outside an interval of f standard deviations from the local mean μ. In practice we use $f = 1.5$.

CLASSIFICATION WITH CBF-NETWORK

Data showing no special distribution in feature space require an universal classification scheme. Nonlinear statistical regression models, like Polynom Classifiers, have been successfully applied to this problem. Also, certain Neural Networks, like the Multilayer-Perceptron (MLP) [3] or the Radial-Basis-Funktions (RBF) [4] belong to this group of universal function approximators. The learning procedure of a MLP is based on a nonlinear optimization of an errorfunction, which may be a critical point. Besides this the RBF shows a more robust behavior, as this problem is reduced to a linear optimization by using local receptive fields in the transferfunction of the hidden neurons. However, this requires an initialization of these neurons by a cluster analysis of the input data.

Our proposed Network is a RBF-Network, using confidences as the response of a neuron derived from the χ^2-distribution of the Mahalanobis Distance (CBF), instead of the commonly used gaussian function:

$$(x - \mu_j)^T C_j (x - \mu_j) = \chi^2_{n,1-\alpha}. \tag{4}$$

μ_j : mean of basisfunction j
C_j : covariance matrix of basisfunction j
n : dimension of data
α : confidence output of basisfunction j

This Network expresses some interesting properities, e.g. the mean μ_j and the covariance matrix C_j can be taken directly from the cluster analysis. A standardization of this function is not neccessary to define the field size, as it is common for Gaussian Networks [5].

A new cluster algorithm was developed to generate the CBF-Network automatically. The algorithm is mainly based on the multivariate Friedman-Rafsky-Test [6] using the assumption of gaussian distributed data. The strategy is to successively divide the cluster until all sub-clusters show good gaussian properties. Besides this uncritical valuation, the test is mainly used to guide the cluster algorithm through the feature space, selecting the most unlikely sub-cluster to be split next.

EXPERIMENTAL RESULTS

All the extracted features are shown in Fig.1 for a sample of SAR data to demonstrate the efficiency and necessity of the extracted features. The first row shows the original data followed by rows showing the extracted features RSD, SHA, LFP and LDA (extracted within a 13 x 13 square). The first two columns show different homogeneous areas in a SAR image to demonstrate the independence of the features from the local mean in SAR images, the third column contains an area with a synthetically increased relative standard deviation which causes a change of the RSD and SHA. The features LFP and LDA show no significant difference, i.e. they are structural features and therefore independent from the local standard deviation. The fourth and fifth column contain structural elements: an urban area and an area with small fields. The corresponding features LDA / LFP are highlighted to indicate the structure type. In the last column small fields with an increased relative standard deviation are shown to demonstrate the difference between SHA—which is highlighted only in the presence of homogeneous small planes—and the LFP which indicates the type of structure and therefore shows no difference in both cases.

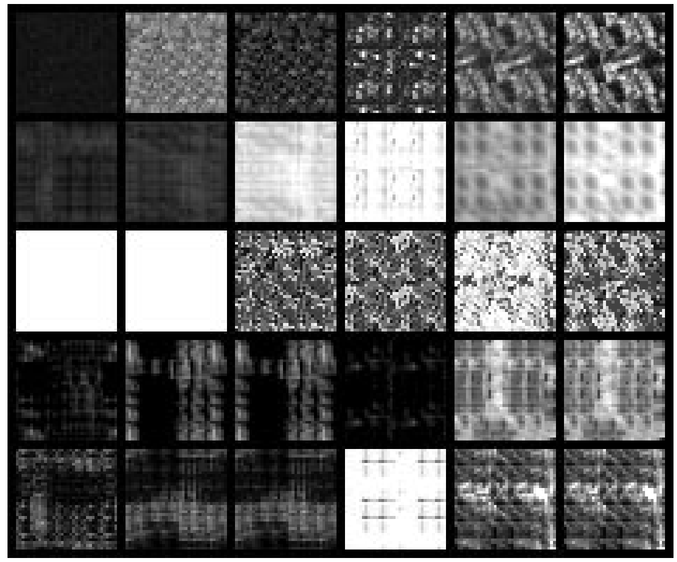

Figure 1: Extracted features from different patterns.

Within our test data set of the size 500 by 500 pixels we had a significant improvement by using the extracted features. Urban areas are classified much better and the confusion of loosely populated urban areas with agricultural areas is nearly eliminated.

REFERENCES

[1] Hagg W., Sties M., "Efficient Speckle Filtering of SAR Images", Proc. International Geoscience and Remote Sensing Symposium, 1994, pp. 2140-2142

[2] Haralick R.M., "Statistical and Structural Approaches to Texture", Proc. of the 4. Int. Conf. on Pattern Recognition, 1978, p. 45

[3] Hornik. K., "Approximation Capabilities of Multilayer Feedforward Networks", Neural Networks, Vol. 4, 1991, pp. 251-257

[4] Hartman E. J., Keeler J. D., Kowalski J. M., "Layered Neural Networks with Gaussian Hidden Units as Universal Approximations", Neural Computation, Vol. 2, 1990, pp. 210-215

[5] Moody J., Darken C. J., "Fast Learning in Networks of Locally-Tuned Processing Units", Neural Computation, Vol. 1, 1989, pp. 281-294

[6] Friedman J. H., Rafsky L. C., "Multivariate generalization of the Wald-Wolfowitz and Smirnov two-sample test", Ann. Statist. Vol. 7, 1979, pp. 697 - 717