Unsupervised Remote Sensing Data Classification Using Multimodal Statistical Model

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Abstract. A solution for the problem of unsupervised recognition in the conditions of a priori indefinite number of object classes in radar images is presented. The designed algorithm performs image clustering to divide image objects into classes. The region of interest is can be chosen by user and then probabilistic filtering is applied to recognize the objects of the predetermined class on the entire image. The algorithm is operated on the multichannel data and shows stable recognition results.

Keywords: image processing, unsupervised classification, remote sensing

1 Introduction

The airborne and spaceborne remote sensing (RS) systems are widely used for ecological monitoring of environment, mapping and extraordinary situation prevention. The analysis of aerospace images allow to detect the waters pollutions such as oil spills, monitor the borders of rivers and lakes, detect ice obstruction, evaluate water resources, soil state and erosion and so on [1]. Aerospace remote sensing of the Earth surface is performed as by radar systems (including polarimetric radars) as in optical an IR bands [2]. Remote sensing data often are represented by multichannel images where the image brightness corresponds to the amplitude of the signal reflected from the sensed surface [3].

For example, the radar image shown Fig. 1 contains many spatially distributed objects whose number a priori is unknown. Object separation and contouring, detection of the similar objects and their classification (object clustering) using the level of reflected signal intensity is one of the goals of the processing of such images. The noise contained in the images is caused by equipment and reflected signal fluctuations, and significantly complicates the image analysis and classification. An automatic image classification requires to determine the number of the classes of the objects that can be distinguished in the analyzed image. The statistical characteristics of the separable objects can be determined for their following recognition in the analyzed and similar images.

The automatic classification can be performed analyzing the local histograms calculated on the data within the sliding on the entire image window (see Fig. 1). The window size must be matched to the RS system resolution. Since in the separated image fragment several objects may be presented, the resulted histogram may be of

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the multimodal character (see Fig. 2). Analyzing the histogram multimodal content one can determine the number of the objects in the separated image fragment.

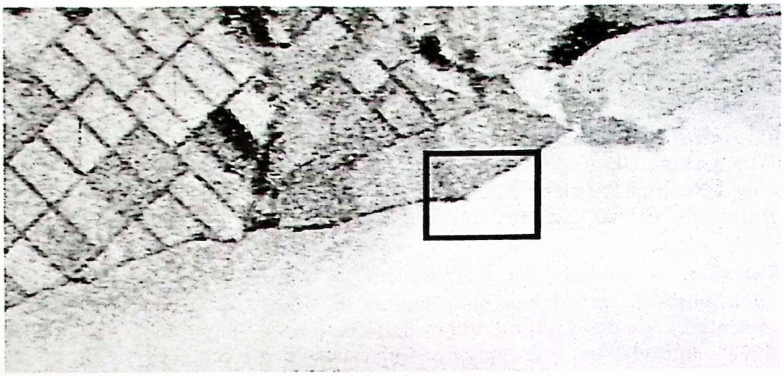

Fig. 1. Fragment of radar image of sea cost (negative).

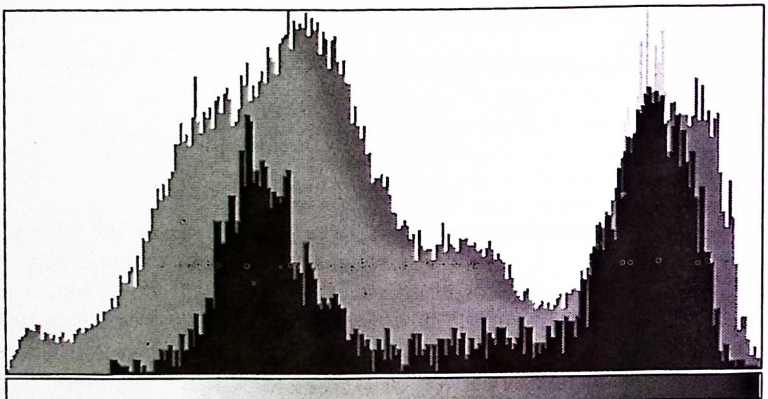

Fig. 2. Histogram of entire image in Fig. 1 (gray) and local window histogram (black).

2 Multimodal Statistical Model

One of the methods of multimodal distribution descriptions is the use of the normal distribution mixtures of the form $f(x)=\sum_{k=1}^{M} p_k \cdot \varphi_k(x)=\sum_{k=1}^{M} p_k \frac{\exp\left\{-\frac{(x-m_k)^2}{2\sigma_k^2}\right\}}{\sqrt{2\pi\sigma_k^2}}$ [4], where M is a number of the normal kernels $\varphi_k(x)$; m_k , σ_k are the parameters of k-th normal distribution $\varphi_k(x)$; p_k are the weight coefficients satisfying the condition $\int f(x)dx=1$.

The procedure of finding parameters M, m_k, σ_k, p_k is based on the minimization of the mean square error of the approximation. Since the true distribution density function is a priori unknown, the number of kernels M necessary to build model, the distribution parameters m_k, σ_k, and the weighting coefficients p_k are also unknown.

In reference [5] a probabilistic approach is proposed to find the estimates of the normalizing coefficients p_k, which consists of the determining of the probability of the appearance of each approximating kernel $\varphi_k(x)$ that can be evaluated on the distribution histogram. However, the implementation of such an approach requires the number of modes in the distribution $h(x)$ to be determined and the sample distribution to be separated onto the contented mixtures.

The determination of the number of modes for the analytical distributions is not a problem because one can find this number solving the following equations: $\frac{\partial h(x)}{\partial x} = 0$, $\frac{\partial^2 h(x)}{\partial x^2} > 0$.

Unfortunately, the non-smooth character of the histograms $h(x)$ that contained the source data for the approximation does not allow the use of the numerical differentiation methods directly for $h(x)$ [6].

Even if the number of modes in the distribution is known, its parameters m_k, σ_k, $k = 1 \ldots M$ of the normal kernels $\varphi_k(x)$ of the distribution mixture $f(x) = \sum_{k=1}^{M} p_k \varphi_k(x)$ are unknown. These parameters can be evaluated only in case when the source sample $h(x)$ can be divided by the data composed by each distribution mode $\varphi_k(x)$ that is equivalent to perform the data clustering in the terms of the recognition theory [7]. This way the sample estimates would contain a significant error.

3 Multimodal Statistical Model Design

The design of the data multimodal statistical model can be performed in several stages. At the first stage it is necessary to determine the number of components M in the distribution mixture. In the presence of several modes in the histogram $h(x)$ of the experimental data, for example, their quantity can be determined by calculating the crosscorrelation between the histogram and an etalon distribution. The crosscorrelation function is used for the reasons that, first, the correlation coefficient characterizes the similarity of one function to another, and second, the change in the parameters of the etalon function allows estimation of the histogram parameters.

If the normal distribution is adopted as an etalon function then the crosscorrelation function can be determined as

$$R(m) = \int_{X\min}^{X\max} h(x) \cdot \varphi(x,m) dx \,. \qquad (1)$$

When the expectation m of the normal distribution $\varphi(x,m)$ varies from $x_{\min}$ to $x_{\max}$ at fixed variance σ^2 value, the maximums of the correlation function (1) correspond to the positions of the modes in the distribution histogram.

The analogous "scanning" can also be performed for the variance of the normal distribution. To this end, the crosscorrelation function at the fixed expectation m of the normal distribution is calculated as follows:

$$R(\sigma) = \int_{X\min}^{X\max} h(x) \cdot \varphi(x,\sigma) dx \qquad (2)$$

The crosscorrelation function (2) is less sensitive to the variance changes because the analyzed distribution has several modes. It is supposed that the most accurate results can be found calculating a bidimensional correlation function. Fig. 3 shows an example of such a function.

$$R(m,\sigma) = \int_{X\min}^{X\max} h(x) \cdot \varphi(x,m,\sigma) dx \qquad (3)$$

To determine the number of distribution modes it is necessary to determine the number of maximums in the bidimensional correlation functions. This problem can be solved differentiating numerically the function $R(m,\sigma)$ and solving the following equations:

$$\frac{\partial R(m,\sigma)}{\partial m} = 0, \frac{\partial R(m,\sigma)}{\partial \sigma} = 0, \frac{\partial^2 R(m,\sigma)}{\partial m \cdot \partial \sigma} > 0 \,. \qquad (4)$$

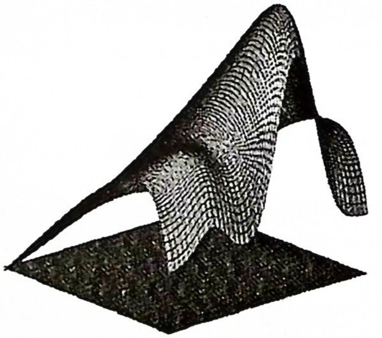

Fig. 3. Two-dimensional cross correlation function (3).

At the second stage the statistical estimates of the parameters m_k, σ_k are determined for each distribution mode $k = 1 \ldots M$. Such a possibility gives a sequential view of the function $R(m,\sigma)$ in the points that it satisfy to the conditions (4) and calculating the corresponding estimates of the values m_k, σ_k.

The third stage consists of finding the weighting coefficients for each distribution mixture components p_k , $k = 1...M$. The interpretation of the weighting coefficients p_k as probabilities of the data belong to the histogram clusters $\varphi_k(x)$ allows building the algorithm for the coefficients p_k determination using the method of the maximum a posteriori probability. For each data sample element x_i one can calculate the probability it drops in the class $\varphi_k(x)$, using the Bayes formula [7]:

$$Q_k(x_i) = \frac{\varphi_k(x_i)}{\sum_{j=1}^{M} \varphi_j(x_i)}. \quad (5)$$

As the parameters of the functions $\varphi_k(x)$ the previously found estimates of m_k, σ_k are used. Then, the maximal value of a posteriori probability $Q_k(x_i)$, $k = 1...M$ is found. The number k determines the number of the cluster $\varphi_k(x)$.

Counting the number of the elements n_k each cluster has the probability estimates that can be determined as follows:

$$p_k = \frac{n_k}{N},$$

where N is a total number of the sample elements.

Clearly, such an approach gives approximated estimates of the probabilities p_k because a priori it is assumed the equiprobable belonging of the element x_i to the class $\varphi_k(x)$. Besides, the considered approach automatically satisfies to the condition $\sum_{k=1}^{M} p_k = 1$.

The estimates of the parameters of the approximating multimodal distribution found according to the described method needs in a more accurate update. To this end, numerical optimization procedures [6] can be used. The cluster parameter estimates m_k , σ_k , p_k can be used as varied parameters in these procedures.

4 RESULTS

4.1 Simulation results on multimodal statistical modeling

To verify the elaborated method, samples were generated having random values of normal distribution with parameters N(10, 2) и N(0.0, 1.5). Then, the samples were mixed in proportion 1/8.

At the stage of the correlation analysis, a two-dimensional correlation function $R(m,\sigma)$ was obtained (see Fig. 3). The analysis of this function detected two clusters with the parameters N(10.02, 2.49) and N(0.26, 1.93) (see Fig. 4). A small bias in the estimates of the normal distributions is caused by mutual influence of the distribution modes at data correlation analysis.

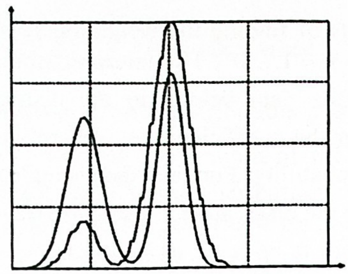

Fig. 4. Results of cluster analysis of bidimensional crosscorrelation function in Fig. 3.

To estimate the weighting coefficients p_k, the probabilities of classification for each element were calculated according to the method of the maximum of a posteriori probability (5). In such a manner, the statistical model was updated as it is shown in Fig. 5: p1 = 0.92, p2 = 0.08.

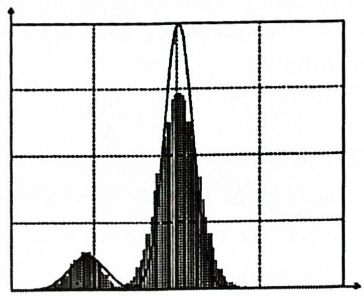

Fig. 5. Cluster probability estimation results.

The resulting values N(10.02, 2.49), p1 = 0.877 and N(0.26, 1.93), p2 = 0.123 were obtained applying a numerical optimization procedure. The shape of the approximating function is shown in Fig. 6.

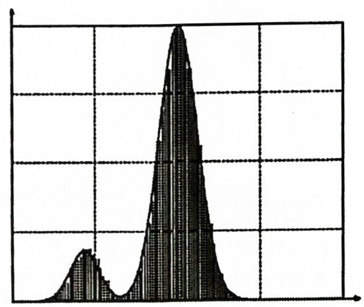

Fig. 6. Statistical model optimization results.

4.2 Results on application of automatic classification algorithm to real data

The proposed classification algorithm based on polynormal distribution was applied to different images. For example, the result of the automatic classification the radar image in Fig. 1 is shown in Fig. 7. Here, the algorithm detected 16 different clusters. Each of them is represented in Fig. 7 by its intensity. Fig. 7 was obtained by application of the probabilistic filters [8], each filter was adjusted properly to its cluster.

The presence of the noise in the original image and the blurred object edges result in erroneous classification of the edges of the homogeneous areas, which may be classified as separate classes. Image prefiltering using low-pass smoothing filters [9] results in the reduction of the number of the separable object classes to 6 (see Fig. 8). It means that objects having different electrophysical nature (for instance, terrain and sea surface) may be classified as belonged to the same class. Therefore, the image preprocessing for subsequent classification needs in detail preserving filters [10] that do not smooth object edges.

The automatic classification of the images of better quality (sharper and less noisy, as, for example, image shown in Fig. 9) produces better results. In the image in Fig. 9 it was found 7 clusters shown in Fig. 10 by the areas of different intensity. The analysis of the classification results shows that in this case the areas of different electrophysical parameters practically are not unified.

5 Conclusions

The presented automatic image classification algorithm can be used to solve the problem of radar image classification in the conditions of a priori ambiguity about the number of the object classes and their statistical properties. The proposed classification algorithm permits to detect the distinguished object classes. The mathematical background for the proposed radar image classification algorithm is the image statistical model that assumes the polynormal distribution of the data. To approximate well the image histogram, it was solved the problem of the determination of the number of the kernels that are the centers of the histogram clusters. The statistical model updated recursively calculates more accurate statistical characteristics of the object classes. The additive components of the statistical model can serve as a description of the classes of the objects contained in the radar image and can be used for their recognition.

The application of the proposed algorithm to real radar images has demonstrated the stability of the proposed automatic classification technique. However, the number of the detected classes depends significantly on the quality of the original image and used preprocessing methods.

Fig. 7. Result of clustering radar image in Fig. 1.

Fig. 8. Result of clustering radar image in Fig. 1 after filtration.

Fig. 9. Image of river mouth.

Fig. 10. Result of classification of image in Fig. 9.

Acknowledgements

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