RECOGNITION OF CLOUD FIELDS IN SATELLITE IMAGES BY THE SEGMENTATION ALGORITHM BASED ON LOCAL HOMOGENEITY OF VIDEODATA

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A new algorithm of segmentation of multispectral videodata using cluster analysis has been proposed. A problem of recognition of transient fragments of videodata is solved to eliminate in the first stage "mixed" pixels from the tutorial algorithm thereby increasing the quality of recognition of the selected classes. An example of recognition of cloud fields in images recorded with the AVHRR of a NOAA satellite demonstrates algorithmic implementation.

One of the initial stages of image interpretation is segmentation, i.e., recognition of homogeneous (in a sense, for example, in intensity) fragments. It should be noted that images with vast homogeneous fragments and clearly defined sharp boundaries are few and far between. One can most frequently see fragments representing transient zones from one class to another. In this case, conventional segmentation methods of clusterization of a complete sample are inefficient, because the number of sample elements, which belong to the transient fragments between classes, is larger than the number of elements which represent a pure class.

In this case, it is necessary to recognize sample elements belonging to individual classes. It would be reasonable to proceed from the following assumptions:

1. A pure class is represented by the parameter vector $\mathbf{X}_0$.

2. There is a small zone ε in the image plane in which the parameter vector is almost constant and can be represented as

$$\mathbf{X}_\varepsilon = \mathbf{X}_0 + \xi ,$$

where $\mathbf{X}_\varepsilon$ is the parameter vector in a certain zone ε, $\mathbf{X}_0$ is the vector typical of its class, and ξ is the random variable with uncorrelated components that obey analogous distributions.

For this model the homogeneity of the given fragment of videodata ε is checked by the agreement between the distributions and uncorrelated components of the vector ξ. With this aim, we sample $\{\mathbf{X}_{\varepsilon i}\}$, $i = 1 \dots n$ from the given test fragment ε and estimate the expectation and covariance matrix for the sample $\{\mathbf{X}_{\varepsilon i}\}$:

$$\hat{\mathbf{X}}_0 = \frac{1}{n} \sum_{i=1}^{n} \mathbf{X}_{\varepsilon i} , \tag{1}$$

$$\mathbf{C} = \frac{1}{n} \sum_{i=1}^{n} (\mathbf{X}_{\varepsilon i} - \hat{\mathbf{X}}_0)\,(\mathbf{X}_{\varepsilon i} - \hat{\mathbf{X}}_0)^t .$$

As known, the covariance matrix can be represented as the following singular expansion:

$$\mathbf{C} = \mathbf{U}\,\Lambda\,\mathbf{U}^t , \tag{2}$$

where Λ is the diagonal matrix of eigenvalues, $\mathbf{U}$ is the matrix of eigenvectors.

To test the agreement between distributions of components of the vector ξ, we calculate the projections of centered vectors of the sample $\{\mathbf{X}_{\varepsilon i}\}$ on the eigenvectors of covariance matrix. Because the sample vector components can be different in nature, we normalize them to the corresponding variances, that is, to the diagonal elements of matrix $\mathbf{C}$, to scale all quantities.

Let $\mathbf{u}_j$ and $\mathbf{u}_k$ be the jth and kth vectors of matrix $\mathbf{U}$, and $\mathbf{C}_1$ be the diagonal matrix comprising the square roots of diagonal elements of matrix $\mathbf{C}$

$$\mathbf{C}_1 = \sqrt{\mathrm{diag}\,\mathbf{C}} .$$

Then the normalized projections of the ith vector of the sample on the jth and kth vectors of matrix $\mathbf{U}$ have the following forms:

$$\eta_{ij} = \mathbf{u}_j^t\,\mathbf{C}_1^{-1}\,(\mathbf{X}_i - \hat{\mathbf{X}}_0) , \qquad \eta_{ik} = \mathbf{u}_k^t\,\mathbf{C}_1^{-1}\,(\mathbf{X}_i - \hat{\mathbf{X}}_0) . \tag{3}$$

We check samples $\{\eta_{ij}\}$ and $\{\eta_{ik}\}$ for the homogeneity with the use of the Kolmogorov-Smirnov test. With this aim, we construct empirical distribution functions $F(\eta_{ij})$ and $G(\eta_{ij})$ for the

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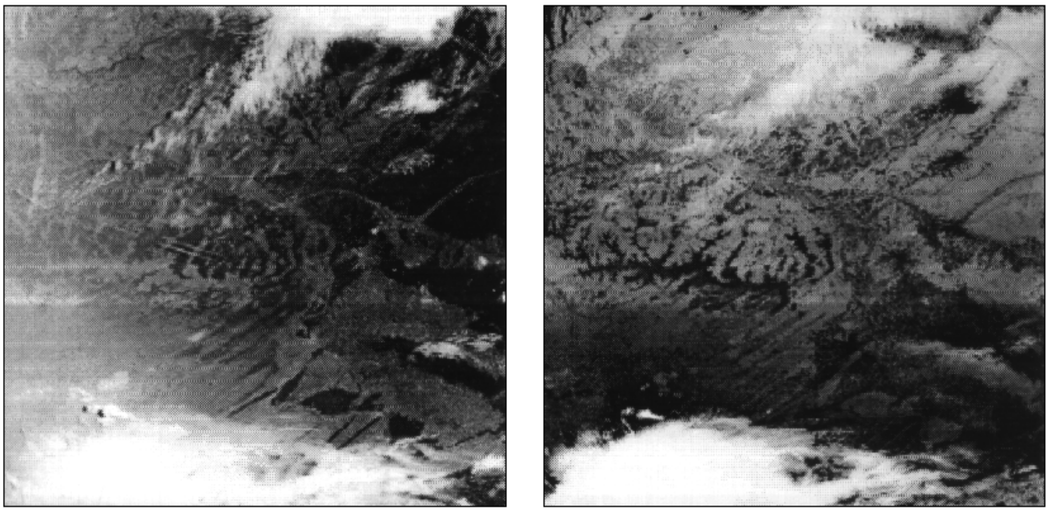
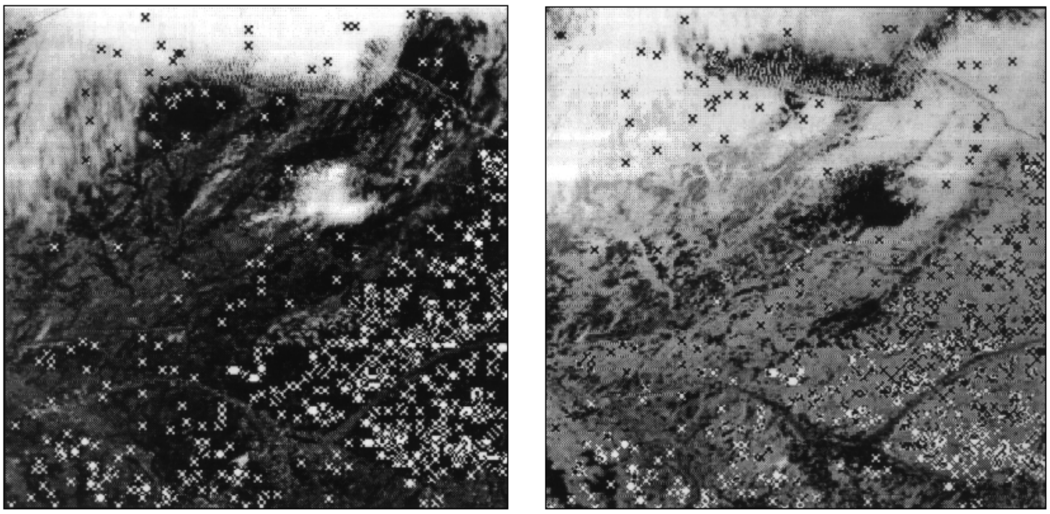


a *b*

FIG. 1.



a *b*

FIG. 2.

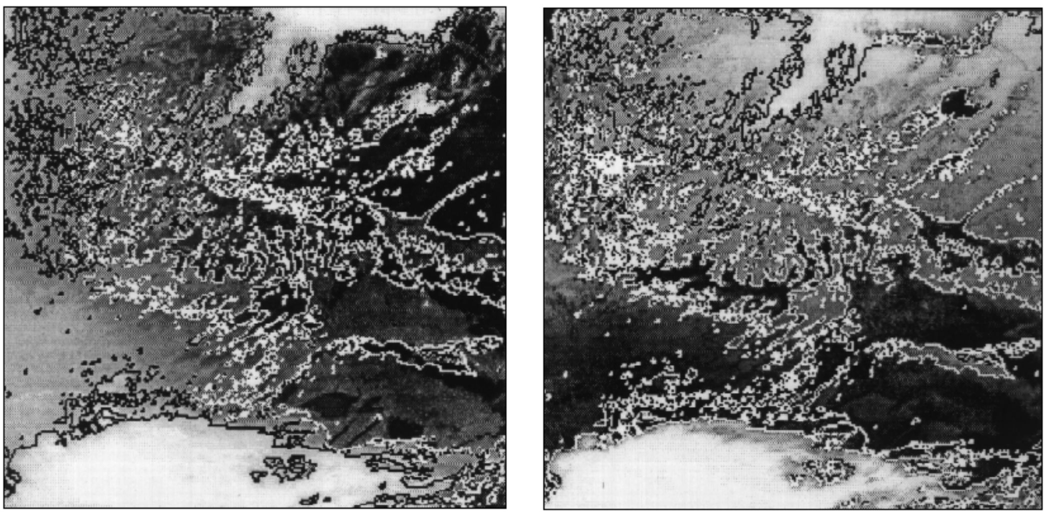


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FIG. 3.

ordered samples $\{\eta_{ij}\}$ and $\{\eta_{ik}\}$ and calculate the statistic:

$$D_i = \sup_{\{j,\, k\}} |G(\eta_{ij}) - F(\eta_{ik})| , \tag{4}$$

which for homogeneous distributions does not exceed a preset value. The critical values D are tabulated (Ref. 1).

The special test for uncorrelated components of vector ξ is not required, because in case of dependent vectors of the initial sample the normalization to the diagonal elements of covariance matrix **C** leads to the disagreement between the distributions of the components of vector ξ.

We obtain the sample $\{\mathbf{X}_{0i}\}$, $i = 1...N$, where N is the number of identified fragments after the recognition of homogeneous fragments in the sense of the above-described model. At the first stage of algorithmic implementation the number N is large, that is why subsequent merging of the obtained subclasses is necessary. Because each class can be represented by several vectors, in the second stage it is necessary to cluster the obtained samples before their classification. To this end, we define a pair of vectors for which the distance

$$d = \min_{\{j,\, k\}} \left(\sqrt{(\mathbf{X}_{0i} - \mathbf{X}_{0j})^t\, (\mathbf{X}_{0i} - \mathbf{X}_{0j})}\right) \tag{5}$$

is minimum and replace them by a new vector

$$\mathbf{X}'_{0k} = \frac{n_i}{n_i + n_j}\,\mathbf{X}_{0i} + \frac{n_j}{n_i + n_j}\,\mathbf{X}_{0j} \ ,$$

$$n_k = n_i + n_j \ .$$

Then we calculate the weight n_k of new vector. We repeat this procedure until the number of sample vectors exceeds the given sought-after number of classes.

The segmentation of the entire data set is finished when each vector is classed with the centers of the corresponding classes by the nearest-neighbor method of the Euclidean metric.

A fragment of five-spectral image of the Earth's surface 1024×1024 pixels shown in Fig. 1 (where *a* and *b* correspond to channels 1 and 3) illustrates the algorithmic implementation.

The result of recognition of homogeneous fragments is displayed in Fig. 2 where crosses indicate the fragments identified by the algorithm (only the right upper fragment of the initial image is shown). The entire fragment was classified after grouping of the obtained vectors in five classes. The results of classification are shown in Fig. 3, from which one can see that segmentation of the clouds, which are countered in the figure, is fairly reliable.

REFERENCES

1. L.N. Bol'shev and N.V. Smirnov, *Tables on Mathematical Statistics*, 3rd ed. (Nauka, Moscow, 1983), 416 pp.