Reconstruction of images taken from space of the Earth's underlying surface obscured by haze and cloud fragments

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We consider a two-stage procedure of correction and reconstruction of images of the Earth's underlying surface recorded with the AVHRR instrument from NOAA satellites in some situations observed in spring and fall seasons. The method of histogram transforms is used at the first stage to eliminate the effect of a semitransparent cloud cover (the stage of data correction). In order to eliminate screening by clouds, the approach based on the data reconstruction using non-parametric regression relations is used at the second stage (the stage of reconstruction). Examples of the correction and reconstruction of the actual images recorded with the AVHRR device are presented.

1. Introduction

The difficulties existing in analysis of videodata obtained in situations when isolated sections of the Earth's surface are obscured by semitransparent haze or cloud fragments are known quite well. The problem arises on reconstructing the portions of videodata which are distorted by the atmosphere. Analysis of images of the underlying surface of the Earth (USE) recorded with a the five-channel AVHRR device from NOAA satellites shows that often only separate sections of analyzed scenes are obscured by semitransparent aerosol formations when the outlines of relief are viewed through them. At the same time in the thermal ranges recorded in channels 3, 4, and 5 these formations manifest themselves as screens. All the variety of other situations connected with the distorting effects of cloud formations is not considered in this case. If an image is not distorted over the main part of the videodata field then the correction for a semitransparent haze within separate sections of sufficiently small areas can be performed based on the approach connected with the transform of brightness histograms. In this case it is proposed that the standard histogram of brightness distribution of an image section observed under "good" visibility conditions is known. Then this section of videodata is recorded under conditions effected by a haze. It causes a compression of the dynamic range of observations and distortion of the histogram shape. A problem is in the conversion of radio brightness of a shaded image so that the corrected image will have a histogram which is similar of the standard histogram.

Another one approach to reconstruction of the localized sections of multichannel videodata is based on the predicting abilities of regression relations describing the interrelationships of physical fields of the radio brightness. In this case a nonlinear regression equation is reconstructed beforehand using the complete sections of image with no distortions present, and then it is used to reconstruct the image sections lost by the screening. In this case it is necessary to provide for the texture (statistical) uniformity of sections of the videodata, that have been selected for teaching (to reconstruct the regression relation), and of the section to be reconstructed, which is distorted or shaded. The investigation of physical models to form a thermal radiation and reflection of day light in the thermal and visible ranges leads to the conclusion that a correlation between their radio brightness exists. Moreover, the account of random factors connected with the change of slope of surface elements causes a positive correlation, and the integral reflection factor of solar radiation causes a negative correlation between the brightness values in the thermal and visible ranges. In the literature[1] analysis of visible and infrared brightness correlation was performed using models and actual objects of the underlying surface of the Earth. It was noticed that the type (positive or negative) and the magnitude of correlation depend on the texture and reflecting properties of the surface. In this connection it is natural to use a nonlinear regression equation to reconstruct the faulty components of one field from observations of the other field.

2. Correction for a semitransparent shading of image fragments by the method of histogram transform

Let us consider the approach based on the method of histogram transform. It is appropriate to use this approach in the cases when the observed image is distorted by a semitransparent aerosol formation, while in addition the brightness distribution histogram of this section of videodata obtained under the conditions of good visibility is known. The latter histogram can be changed by a histogram of an adjacent section of the image if it is equivalent by texture to that under

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reconstruction and is not shaded on the given image. Note, that the image histogram as a statistically mean characteristics is more stable as compared with a specific sample of observations.

Allowing for the resolution of the AVHRR instrument when a 1 × 1 km section of the underlying surface is mapped into a pixel of videodata the model of shading effect on the surface image in the mathematical sense has a form of a convolution operator. The point spread function for semitransparent aerosols which are adjacent to the reflecting surface has the delta-component and an extended spectrum and it is unknown. Let us make an attempt to describe this situation with histograms. We will assume that the ideal conditions for observing some sections of the Earth surface form the radio brightness distribution described by the histogram $\hat{g}(y)$, and the effect of semitransparent haze causes a distortion of the histogram $\hat{g}(y)$ so that we observe the brightness distribution $\hat{f}(x)$ with a decreased dynamic range and displaced domain of the videodata definition.

For simplicity let us first assume that x and y are continuous values, $x, y \in [0,1]$. The radio brightness distribution of a shaded image will be described by the probability density function $f(x)$, and the radio brightness distribution of an ideal (standard) image will be described by the distribution $g(x)$. To reconstruct the image, we use the transforms of the brightness

$$y = T(x), \quad x, y \in [0,1], \tag{1}$$

where x are the values of brightness of a shaded image, and y are the values of the clear image brightness.

We shall consider the class of reconstructing transforms $T(.)$ which are unambiguous and strictly monotonic on the interval [0, 1]. Thus the inverse transform $T^{-1}(.)$ will also be strictly monotonic on [0, 1]. The monotony condition preserves the order of change from the black to white in the brightness scale of a reconstructed image.

Allowing for the fact that the values x and y are functionally related, their probability distributions are expressed in the following way[2]:

$$g(x) = f(x) \left| \frac{dx}{dy} \right|_{x=T^{-1}(y)}, \tag{2}$$

where $T^{-1}(.)$ is the inverse transform.

To find the transform $y = T(x)$, let us consider the following two-stage procedure of identifying $y = T(x)$ (see Refs. 2 and 3). Let us make use of the property of integral distribution function, integrated as a transform, to smooth the frequencies, namely

$$t = F(x) = \int_0^x f(s)\, ds, \tag{3}$$

where $F(x)$ is the integral distribution function, t is distributed uniformly on the interval [0, 1]. On the other hand by analogy with the expression (3) we have

$$t = G(y) = \int_0^y g(s)\, ds,$$

where $G(y)$ is the integral distribution function. Equating these expressions, $G(y) = F(x)$, we obtain

$$y = T(x) = G^{-1}[F(x)], \tag{4}$$

where $G^{-1}(y)$ is the inverse transform.

Thus, changing at the first stage to the uniform brightness distribution by the formula (3), and inverting, at the second stage, the transform $G(.)$ we obtain the unknown brightness distribution and expression for correcting the transform $y = T(x)$.

Then we consider a discrete version of the transforms (4). Let $X = \{X_i\}_{i=1}^n$ be a fragment of the image with the assigned numerical values (the fragment is not obligatory rectangular) and n is the number of pixels within this fragment. Let us assume that this fragment is distorted by the atmosphere, and $Y = \{Y_i\}_{i=1}^n$ is the fragment of data with assigned numerical values recorded under "good" visibility conditions. This fragment allows the histogram $\hat{g}(y)$ to be reconstructed.

When the brightness levels take discrete values, the expression (3) has a table form[3]:

$$t_k = \hat{F}(x_k) = \sum_{j=0}^{k} \hat{f}(x_j) = \sum_{j=0}^{k} \frac{n_j}{n},$$
$$0 \le x_j \le 1,\ k = 0, \ldots, L-1, \tag{5}$$

where L is the number of discrete brightness levels; n_j is the number of elements from the total number n which have a level j in the discrete image.

Accordingly, a discrete form of the expression (4) is as follows:

$$t_k = \hat{G}(y_k) = \sum_{j=0}^{k} \hat{g}(y_j) = \sum_{j=0}^{k} \frac{n_j}{n},$$
$$0 \le y_j \le 1,\ k = 0, \ldots, L-1. \tag{6}$$

Therefore, the conversion of such a function is achieved by rearranging the input and output and together with expression (5) can be used to correct the radio brightness by the method of histogram transform.

3. Reconstruction of images based on the regression equations of prediction of random fields of radio brightness

Let us consider the approach to videodata reconstruction based on the regression relationship. To construct the regression equation, it is necessary to have a clear (undistorted) fragment of an image which is put into the point by point correspondence with the reconstructed section of videodata. Moreover, to adapt the equation to specific videodata, the section of undistorted videodata recorded in two channels simultaneously is needed (we call such a fragment as teaching).

We will describe the values of the predicted field that is being reconstructed by a random value $Y \in R^1$, and the radio brightness of the fields, which are the sources of information for prediction will be described by the random vector $\mathbf{X} \in R^k$, where R^k is the k-dimensional Euclidean space; $\mathbf{X} = (X^1, \ldots, X^k)^{\mathrm{T}}$, X^i are the radio brightness measured in the ith channel of the AVHRR instrument, $i = 1, \ldots, k = 5$, T is the transposition sign.

Interrelation of the predicted variable Y and vector $\mathbf{X}$ we will describe by the regression functional

$$m(\mathbf{x}) = E(Y / \mathbf{X} = \mathbf{x}), \qquad (7)$$

where $E(.)$ is the operator of mathematical expectation, and $E(|Y|) < \infty$.

If the following probability densities of the random values $\mathbf{X}$ and Y exist, then allowing for Eq. (7) we have

$$y = m(\mathbf{x}) = \int_{R^1} y \frac{f(\mathbf{x}, y)}{f(\mathbf{x})\, f(y)} \mathrm{d}F(y), \qquad (8)$$

where $\mathbf{x} \in R^k$, $y \in R^1$, $f(\mathbf{x}, y)$ is the simultaneous probability density of the vector $\mathbf{X}$ and value Y; $f(\mathbf{x})$ is the probability density of the random vector $\mathbf{X}$; $f(y)$ is the probability density of the random value Y, and $F(y)$ is the distribution function of Y.

If we have a sample of random independent, in pair, values and equally distributed $\{(\mathbf{X}_i, Y_i)\}_{i=1}^n$, where n is the number of check readouts on the test section then to calculate the expression (7), it is natural to use non-parametrical estimates of unknown distributions using selected data.[4] Let us change the unknown distributions for their non-parametrical estimates of the kernel type, and $F(y)$ by the empirical function $F_n(y)$. Then the estimate of the regression equation (8) takes the form

$$\hat{m}_h(\mathbf{x}) = \sum_{l=1}^{n} \frac{Y_l \sum\limits_{j=1}^{n} K_h\,(Y_l - Y_j) \prod\limits_{i=1}^{k} K_h\,(x_i - X_j^i)}{\sum\limits_{j=1}^{n} \prod\limits_{i=1}^{k} K_h\,(x_i - X_j^i) \sum\limits_{i=1}^{n} K_h\,(Y_l - Y_i)}, \qquad (9)$$

where h is the width of a window (smoothing or scale parameter) described by the function $K_h(u) = h^{-1} \times K(u/h)$. The Epanechnikov kernel of the following form: $K_h(u) = 0.75\,(1 - u^2)\, I(|u| \le 1)$, where $I(.)$ is the indicator function or the Gaussian kernel, is taken as $K(.)$.[4]

The practical experience of using similar estimates shows that the accuracy characteristics of the regression equation $\hat{m}_h(\mathbf{x})$ are determined to a greater degree not by the kernel form but by the scale parameter h. In this connection the problem arises on estimating h allowing for the particular sample of observations $\{(\mathbf{X}_i, Y_i)\}_{i=1}^n$.

To estimate h, let us use the method of sliding control which assumes that a modified estimate is constructed of the regression $\hat{m}_{hj}(\mathbf{X}_j)$, in which the jth observation is consecutively omitted, $(\mathbf{X}_j, Y_j)$, $j = 1, \ldots, n$. This observation Y_j at the point $\mathbf{X}_j$ must be reconstructed all other observations $\{(\mathbf{X}_i, Y_i)\}_{i \ne j}$ which enters the equation (9) in the best way. The performance criterion for estimate of h depends on the ability to predict the set of values$\{Y_j\}_{j=1}^n$ by the set of samples $\{(\mathbf{X}_i, Y_i)\}_{i \ne j}$:

$$J(h) = n^{-1} \sum_{j=1}^{n} [Y_j - \hat{m}_{h,j}(\mathbf{X}_j)]^2\, w(\mathbf{X}_j), \qquad (10)$$

where $w(.)$ is the weighting function that in the simplest cases can be not used (proposed to be equal to unity). The problem of optimizing the estimate (10) by the parameter h is solved numerically by the search method of adaptation.[5]

After the parameter h in the expression (9) for $\hat{m}_h(\mathbf{x})$ is specified the regression equation can be used to reconstruct the values Y by the observed $\mathbf{X}$ for the fragment of videodata obscured by clouds. Note that the regression model of prediction of unobserved values will only work if the statistical uniformity holds of the data which are used to reconstruct the relation and of those that are to be reconstructed. For this preliminary analysis of the “complete” image by a segmentation algorithm enabling one to select statistically uniform sections is necessary. Then it is necessary to reconstruct the local expression (9) with its values of h at every of such sections.

4. Correction and reconstruction of the images of the underlying Earth’s surface recorded with the AVHRR instrument

The problem of atmospheric correction in a general statement is sufficiently complex, and the considered approaches are oriented on some particular situations of the atmospheric distortions which occur in practice. So, when the underlying surface of the Earth is recorded in fall and spring periods, we often observe the following picture. In the 1st and 2nd observation channels we note a semitransparent shading of some sections of the videodata. At the same time in the 3rd, 4th, and 5th channels we have a complete screening of these image fragments by thermal anomalies. At the same time the sections of similar texture and the absence of shading exist on the images. This similarity principle is a pre-condition for using the developed approaches. At the first stage of the reconstruction of such images we perform a correction of sections with the semitransparent shading by the method of histogram transform. For this we choose two texture-uniform image fragments selected in Fig. 1, one of them is “clear” and another one shaded and hence it is to be corrected.

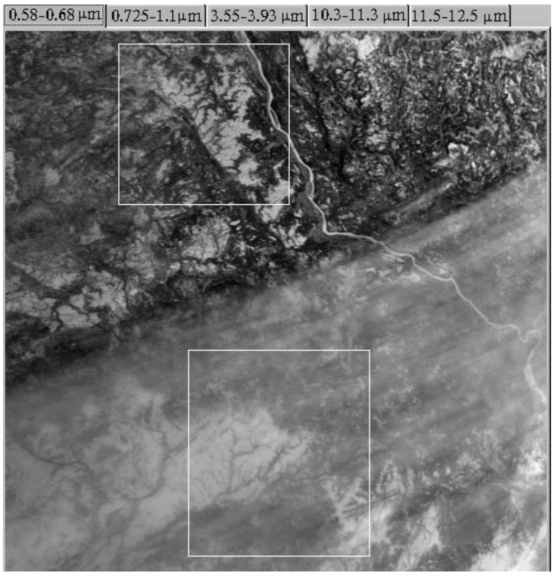

Fig. 1*a*. The image of 1st channel with the example of semitransparent shading of a part of the image and selection of the standard (at the top) and reconstructed (at the bottom) fragments.

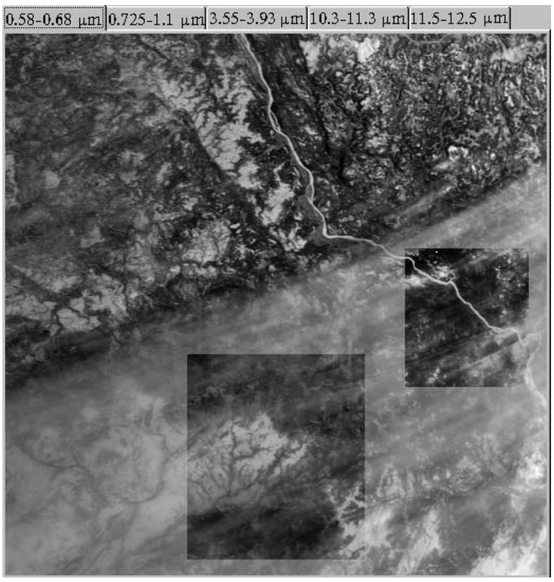

Fig. 1*b*. The example of corrected fragments of the 1st and 2nd channels of the image by the method of histogram transform.

We estimate the histograms from both sections (Figs. 2*a* and *b*) and from the relation (4), and correct the shaded fragment based on this relation. The result of correction is presented in Fig. 1*b*. The quality of thus obtained image can be estimated by the degree of adequacy between the standard histogram and the histogram of the corrected image (Figs. 2*a* and *c*). One should take into account the line character of the latter histogram what is connected with the discreteness of brightness of the transformed image, while the theoretical grounds of the approach are correct for the continuous interpretation. This effect manifests itself in that the integral performance criterion gives slightly overestimated values because of the absence of some values of brightness in the corrected image.

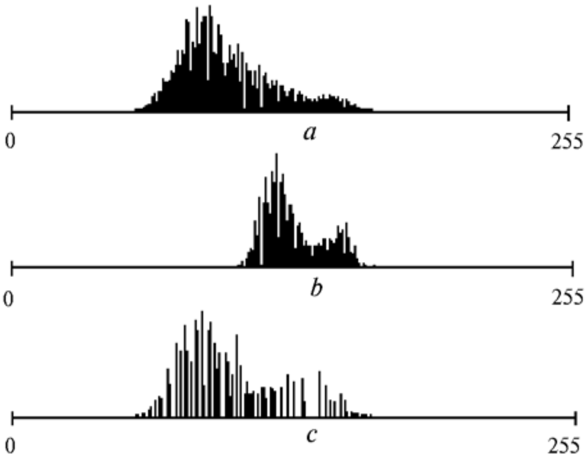

Fig. 2. Histograms of the image fragments presented in Fig. 1*a*: a standard section (*a*), a semitransparent shaded fragment (*b*), and the reconstructed fragment (*c*).

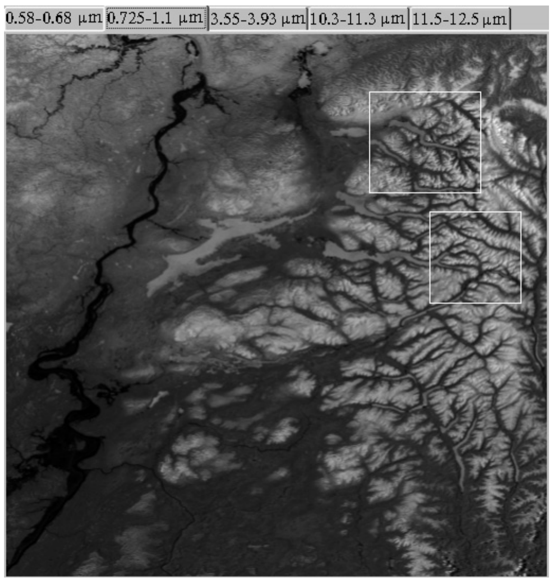

Fig. 3. The clear spring image in the 2nd channel “Putoran plateau” with a selected fragment for "teaching" of the reconstructing regression (at the top) and in the control fragment.

Then the stochastic relations of radio brightness of the AVHRR channels, which were reconstructed using non-parametric equations of nonlinear regression were investigated. For this a 512×512 readouts section of image in five channels (Fig. 3) was selected, the regression equations were reconstructed using a teaching fragment, and the problem of reconstructing the data in 2nd, 3d, 4th, and 5th channels by the observations in the 1st channel in the control fragment (Figs. 3 and 4) was solved. The regression equations were reconstructed using the teaching fragment by the method of sliding control. In this case the value of the functional of the sliding control (10) was 3.4%. Then the reconstructed regression relations were applied to another one fragment which is similar in texture, and the similarity property was determined approximately by an operator manually (in this case the procedure of cluster analysis can be used, and the similarity zones can selected automatically). The quality of prediction in the spectral channels within another fragment different from the teaching one was 3.4% also.

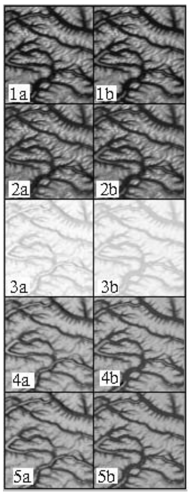

Fig. 4. The initial (*a*) and reconstructed (*b*) image fragments (presented in Fig. 3) using five channels, respectively.

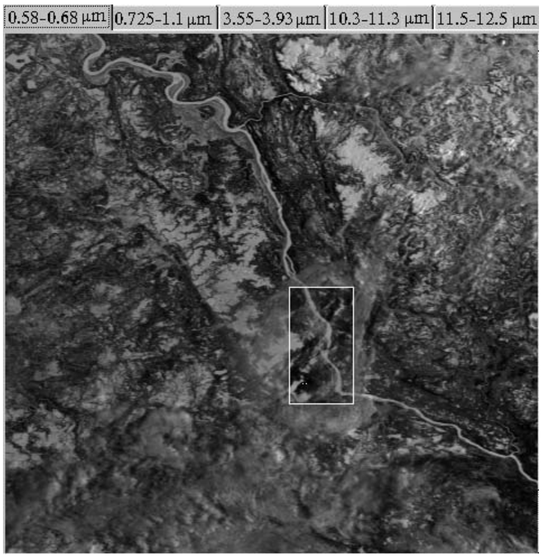

Fig. 5*a*. Correction for a semitransparent shading in the image center by the method of histogram transform (channels 1 and 2).

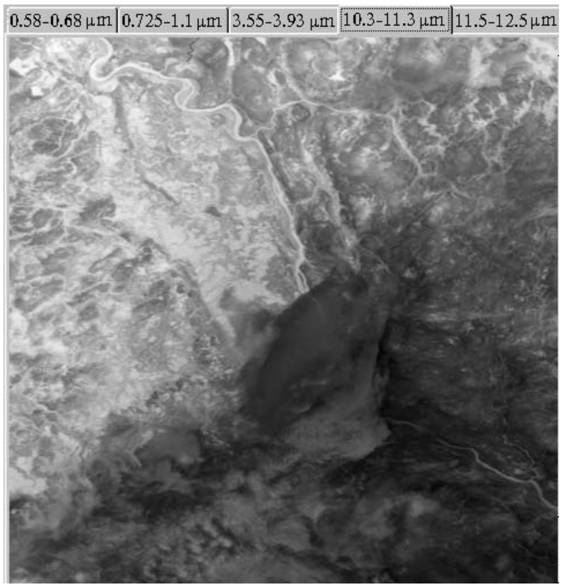

Fig. 5*b*. The example of screening of the underlying surface of the Earth by the thermal anomaly in the 4th and 5th channels.

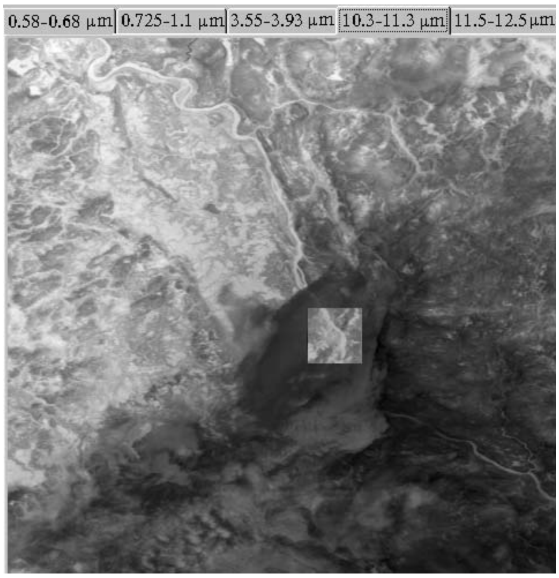

Fig. 5*c*. The example of reconstruction of the screened section of an image in the 4th and 5th channels by the method of regression prediction.

Figures 5*a*, *b*, and *c* show the complete cycle of the two-stage procedure of correction and reconstruction: Figure 5*a* presents the fragment of the histogram correction of a semitransparent shading in the 1st (2nd) channel, Figure 5*b* presents the screening thermal cloud in the 4th (and 5th) channel which was semitransparent in the 1st channel. Finally, the Figure 5*c* shows the image in the 4th channel reconstructed using the non-parametric regression equation.

4. Conclusion

High performance of the approach to reconstruction of images with the regression relation was demonstrated using the fall and spring AVHRR images only. In the case of summer images the reconstruction quality in the 2nd channel by the data from the 1st channel was unsatisfactory. But with summer images we were unable to observe the described effect of semitransparent shading (in the 1st and 2nd channels) and screening (in 3rd and 5th channels) which were corrected and reconstructed in the given case.

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