Detection and identification of objects on multispectral satellite images

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Abstract. This article considers the detection of objects on the time sequences of satellite multizone images. Optimal and quasi-optimal detection algorithms are built on the basis of a combination of non-linear double stochastic filters and pseudo-gradient procedures. The analysis of behavior of the synthesized algorithms at processing of the real satellite material under conditions of a priori uncertainty concerning parameters of deformation of the reference image is carried out.

1. Introduction

The tasks of detecting objects (useful signals) and evaluating their parameters on multidimensional images are of particular interest for a number of applications. Such tasks arise, for example, in the processing of video sequences, medical images obtained by computed tomography, satellite multispectral images of the Earth's surface, etc. [1-5]. Classic examples of such processing are the detection of fires on satellite images, new growths on medical images or new objects on video frames.

The approaches used to detect objects in images and to identify their parameters are very diverse. The most popular methods in recent years have been those based on the use of neural networks. In particular, the algorithm of expanding neural gas and feature description based on histograms of oriented gradients are used in [6] for the task of human detection. In [7], skeleton-geodetic histograms of thickness-distance histograms are used to isolate contours and skeletonize the desired objects, which provides invariance to flexible deformations of images of objects. The use of morphlet trees allows to combine the solution of detection and segmentation problems without preliminary training [8]. An alternative to the above methods is the detection and analysis of descriptors, which is used, for example, in [9]. Here, the descriptor is built on the basis of the graph, the vertices of which are the centers of mass of the peculiarities segments. The advantage of this approach when searching for objects is the invariance to image rotation up to 50 degrees. The general disadvantage of the above approaches is the limitation of the types of detectable objects, as well as the difficulties arising in assessing the effectiveness of detection in different conditions. Let us consider the approach aimed at eliminating this disadvantage, in which the detection of an object is considered as a task of distinguishing between two hypotheses about the presence or absence of an object in a certain area of the image.
The observation model, which is most commonly used in the detection of [3], is an additive mixture of correlated background signal, white noise and useful signal readings. It has been shown in [4] that if a similar observation model is valid and the conditional distributions of observations in the presence or absence of a useful signal can be approximated by the Gaussian ones, the decisive rule of the optimal detector against the background of a multivariate random field takes the form:

$$L = \sum_{j \in G_{ij}} \Delta_j, \begin{cases} L > L_o, & \text{there is a signal;} \\ L < L_o, & \text{no signal,} \end{cases}$$

where $$s_j$$ - countdown of a useful signal at a point with coordinates $$\tilde{i} = (i_1, ..., i_N);$$

$$\Delta_j = \sum_{j \in G_{ij}} V^{-1}(z_j - \hat{x}_j) - \text{filtration error at the point } \tilde{i} \text{ normalized in terms of noise dispersion } \theta_i;$$

$$G_{ij}$$ - the area for which the signal hypothesis is being tested; $$N$$ - the number of measurements of a random field (RF).

The direct analysis of the decisive rule (1) shows that its application is connected with the necessity of preliminary filtration of the RF and the availability of a priori information about all the useful signal samples. Unfortunately, the use of conventional linear filters to process real spatially heterogeneous signals, such as multispectral satellite images, leads to significant errors. The way out here can be the use of non-linear double stochastic (DS) filtration [4, 5]. The use of tensor filters for processing time sequences of multizone images is considered in [5]. It is shown that the use of DS filters for such sequences allows achieving better results than, for example, LPA/ICI filters or wavelet filters. At the same time DS filters together with processing results allow to obtain corresponding covariance functions of filtration errors, which is one of the necessary conditions for evaluation of efficiency characteristics (1).

2. Object Detection Algorithm

Now let's consider the situations connected with a priori uncertainty concerning the signal parameters $$s_j$$. Let's consider that the object is obviously absent from $$(T-1)$$-multi-zone image in the time sequence, but may be present at $$T$$-to the image. We will also consider that we know the shape and structure of the useful signal, but do not know its intensity level in each of the spectral ranges $$s^k$$, $$k = 1, ..., K$$, as well as the actual angle of rotation of the object $$\varphi$$, its scale $$\mu$$ and the geometric center displacement vector $$\hat{h} = (h_x, h_y)^T$$. For this case, the model of observations in the presence of a useful signal (hypothesis $$H_1$$) will be written in the form:

$$z_{i,j}^{k,T} = x_{i,j}^{k,T} + F(s^k, h_x, h_y, \varphi, \mu) + \theta_{i,j}^{k,T}, \quad k = 1, 2, ..., N, \quad (i, j) \in G_{ij}^k, \quad \Delta_{i,j} = z_{i,j}^{k,T} + \theta_{i,j}^{k,T}, \quad k = 1, 2, ..., N, \quad (i, j) \notin G_{ij}^k,$$

$$z_{i,j}^{k,T} = x_{i,j}^{k,T} + \theta_{i,j}^{k,T}, \quad k = 1, 2, ..., N, \quad t = 1, ..., T-1,$$

where $$f_{ij}^k$$ - the samples that define the shape and structure of the object to be detected in $$k$$-of the spectral zone; $$G_{ij}^k = F(G_{ij}^k, h_x, h_y, \varphi, \mu)$$ - the area that the reference object occupies when it is shifted by $$h_x$$ and $$h_y$$ by spatial coordinates, angle rotation, and changing the scale in one time; $$F(\cdot)$$ - affine coordinate transformation [3, 4]. Then, using the modified likelihood ratio method, we can write the following crucial rule:

$$L = \max_{h_x, h_y, \varphi, \mu} \omega(z_{k,T}^{i,j}), \quad (i, j, k) \in F(G_{ij}^k, h_x, h_y, \varphi, \mu) \big| H_1 \big) \begin{cases} L > L_o, & \text{there is a signal;} \\ L < L_o, & \text{no signal.} \end{cases}$$

As before, considering the distribution of observations close to Gaussian, after simple but cumbersome calculations we get the following detector:
where $\tilde{f}_{j,l}^k = F(f_{j,l}^k, h, \phi, \mu)$ and the levels $\hat{z}^k$ can be determined from a system of linear equations:

$$\sum_{k=1}^{N} \sum_{i,j} f_{i,j}^l V_{i,j}^l \triangleleft \tilde{f}_{i,j}^l = \sum_{k=1}^{N} \sum_{i,j} f_{i,j}^l V_{i,j}^l (z_{i,j}^k - \hat{z}_{i,j}^k), \quad t = 1, 2, ..., N.$$ 

In this variant, the detection task can be interpreted as a task of identifying images of objects by template, which in turn can be reduced to the search of spatial transformation, which minimizes the distance between the desired image and the template in a given metric space. One of the methods implementing this approach is the method of pseudo gradient identification (PGI) [10], in which the $\hat{a} = (h, h, \phi, \mu)$ identifications are searched recurrently with the template unchanged:

$$\hat{a}_t = \hat{a}_{t-1} - \Lambda_t \hat{p}_t,$$

where $\hat{p}_t$ – pseudo gradient of the target function, depending on $\hat{a}_{t-1}$ and from the iteration number $t = 0, T$; $\Lambda_t$ - gain matrix [11, 12].

For illustration and analysis of the presented algorithm, we present a fragment of a satellite image (Figure 1a) of the Volga River basin obtained from Landsat 8 spacecraft in the visible spectral range (Channel 2), and the difference between this fragment and the result of joint stochastic filtration of these observations and two previous multizone images (Figure 1b). For convenience of displaying the image in Figure 1b was subjected to the procedure of white noise suppression and histogram stretching.

![Figure 1](image.png)

**Figure 1.** Example of a satellite image and associated artificial image $\hat{z}_{i,j}^k$.

The figure shows the coastline and the object in the center of the image. These are the areas that have undergone the greatest changes over the time of recording the sequence of multispectral images. Changes in shoreline are due to changes in river level, and the object is a vessel recorded in the last multispectral image. If the object of detection is a vessel and its approximate dimensions in the image are known, the spectral mismatch algorithm can be used to select the area of its location in the image [1].

Figure 2 shows a separate artificial frame of the multizonal image obtained by superimposing on the initial image the areas selected at the stage of spectral mismatch analysis.

To apply the algorithm (3) and identify the selected objects, the image library was used (Figure 3). For each of the templates, an approximate spatial size of the object was defined. According to this size and spatial resolution of the satellite image, preliminary estimations of the scale factor were chosen. In accordance with these coefficients, groups of template images were formed on the basis of reference images to cover the entire range of values with the PGI working range. As the researches have shown, 4 template images of the type "swimmers" with initial parameters are enough on the parameter of rotation angle: $\varphi = 0^\circ$, $\varphi = 90^\circ$, $\varphi = 180^\circ$, $\varphi = 360^\circ$. In order to increase the rate of convergence of
estimations and to extend the working range of PGI to the obtained template images, low-frequency filtration of Gauss was applied [13].

As a result of identification of the objects under study "a" and "b" by the PGI method the following values were obtained. The object "a" is a barge type swimming device (95.9% correlation). Azimuth directions of the object under study $\phi_0 = -17^\circ$. The object "b" is a dry-cargo floating device (91.4% correlation). Azimuth directions of the object under study $\phi_0 = 74^\circ$. Figure 4 shows the dependencies of the mathematical expectation estimates $m_{\Delta e} = \left(\text{mes} \, \bar{G}_{i,j}^{k,l,x} \right) \sum_{i,j,k,l,x} (z_{i,j} - \bar{z}_{i,j})$ from the iteration number of the implemented PG procedure.

Figure 2. Selected areas in the background of the original image.

Figure 3. Object Templates.

Figure 4. Study of the convergence process for object "a" and "b" respectively.
To estimate the quantitative characteristics of the efficiency of the proposed algorithm, let's consider some situations that may occur when the object "a" is detected. In the first situation, we will assume that we know all the parameters of the detected object $\vec{a} = (h_s, h_j, \varphi, \mu)$ except for its brightness $s^k$. In the second situation, let's assume that the available information regarding the angle of rotation of the object $\varphi$ is wrong. For the sake of certainty, let's assume that the true meaning $\varphi$ and its valuation differs by $90^\circ$. In the third situation, we will additionally assume that the location information, namely the estimates, is incorrect $\hat{h}_s, \hat{h}_j$ differ from the true values by 3 pixels each.

Figure 5 shows the dependencies of the probability of correct detection on the average brightness coefficient of the object on all frames of the multispectral image for the specified situations when using the algorithm (3). In all cases, the possibility of a false alarm $P_f = 0.0001$.

![Figure 5. Comparison of the effectiveness of detection algorithms in different situations.](image)

3. Conclusion
The obtained results testify to the similarity of the characteristics of the synthesized detector (3), operating under conditions of a priori uncertainty with respect to the parameter vector $\vec{a} = (h_s, h_j, \varphi, \mu)$ and the algorithm (1), in a situation where information about parameters $\vec{a}$ a priori known. If some of this information is unknown or incorrect, the algorithm (3) is preferable. Okay, with the probability of the right detection $P_d = 0.5$ in case of incorrect information regarding the angle of rotation and center of the object, the gain in the level of useful signal at the detector (3) was about 73%.

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