

# Small Objects Detection in Two-Color Images with Spatially Non-Stationary Background

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**Abstract.** A method for improving the reliability of detecting low-contrast small-sized objects in two-color images is considered by pre-suppressing their spatial-non-stationary background. Suppression is carried out by constructing a locally stationary background model using an optimal linear prediction. It is shown how the joint processing of images pair obtained in different spectral ranges affects the detection probability for a given false alarm probability

**Keywords:** low-contrast small-sized objects detection; spatially non-stationary background; two-color images; optimal linear prediction.

## 1 Introduction

One of the frequently formulated requirements in the problem of early potentially dangerous objects detection and processes on the Earth's surface from images obtained by equipment placed on various media is the need to highlight weak anomalies in the recorded parameter (brightness, color intensity, wavelength, etc.) comparable in size to the size of the recording optical system the point scattering function (PSF). If the image background component is spatially stationary, the problem of finding such anomalies can be solved by matched image filtering, taking into account the background correlation properties and the shape of the optical system scattering spot. However, if the image background component does not obey the spatially stationary model, matched filtering will not provide an efficient anomaly identification. In this case, when small-sized, low-contrast anomalies are detected, preliminary the spatially unsteady background component suppression is applied. Let the analyzed image be represented in the form

$$D(i, j) = F(i, j) + A \cdot O(i - i_0, j - j_0) + \xi(i, j), \quad (1)$$

where  $F(i, j)$  is an image background component,  $O(i - i_0, j - j_0)$  – object image with amplitude  $A$  centered in point  $(i_0, j_0)$ ,  $\xi(i, j)$  – random uncorrelated recording noise. Then, knowing the background component model  $\hat{F}(i, j)$ , it is advisable to search for objects in the modified image

$$\tilde{D}(i, j) = F(i, j) + A \cdot O(i - i_0, j - j_0) + \xi(i, j) - \hat{F}(i, j) = A \cdot O(i - i_0, j - j_0) + \theta(i, j). \quad (2)$$

Here  $\theta(i, j) = F(i, j) - \hat{F}(i, j) + \xi(i, j)$  is the disturbance, consisting the residual part of the background, the spatial correlation of which is significantly weakened if the model is chosen successfully, and the original image noise component.

Very effective means of suppression is inter-frame processing, when the model of the background component of the analyzed frame is estimated from previously obtained images of the same area [1-3]. If the previous image is unavailable, the suppression is based on background model prediction on the current image fragment in the neighborhood suspected anomalies. This work is devoted to the study the possibility of constructing a model using the optimal linear prediction (OLP) [4] and the application of this approach when analyzing images pair of the same scene obtained in different spectral ranges.

## 2 Building a background model using OLP

Based on the optimal linear prediction, a locally stationary background model at the point  $(i, j)$  is a linear combination of image samples in the this point neighborhood  $W$

$$F(i', j') = \sum_{i, j \in W} D(i - i', j - j') h(i, j). \quad (3)$$

Here  $h(i, j)$  is the set of weighting coefficients, which are defined as

$$\hat{\mathbf{h}} = \underset{\mathbf{h}}{\operatorname{argmin}} \left\{ \sum_{i', j' \in \Omega} [D(i', j') - \mathbf{h}^T \mathbf{d}_{i', j'}]^2 \right\}, \quad (4)$$

$\mathbf{d}_{i', j'}$  is the vector consisting of lexicographically ordered samples of the point  $(i', j')$  neighborhood  $W$ ,  $\mathbf{h}$  is similarly ordered weighting coefficients vector, and  $\Omega$  is the background stationarity region. To exclude the influence of the object, which may appear at the point  $(i', j')$ , this point itself and its nearest neighbors are not included in the neighborhood  $W$ . It is quite obvious that the worst background suppression will be in the image areas where the background spatial stationarity is violated, in particular, in the region of the brightness sharp changes. Therefore, the stationary region  $\Omega$  cannot be too large.

### 3 Joint image processing

The proposed method for detecting small objects in two-color images consists in a images joint analysis of two spectral ranges pre-modified according to expression (2). It is assumed that the object spectral range overlaps both analyzed ranges. The basic structural image features suppression of the in each channel with its local models leads to decreasing interchannel correlation of the background component, while maintaining the correlation between the images of objects. With joint processing, due to this, we can expect a decrease in the false alarm probability, or, with a given false alarm probability, an increase in the detection probability. The most effective way of joint processing would be to build a common locally stationary background model similar to (4), in which  $\mathbf{d}_{i', j'}$  contains appropriately ordered points of two images. The problem is that with a twofold increasing weight coefficients vector  $\mathbf{h}$ , the computational cost of its estimating increases many times. Therefore, for each color, its own background model was built independently, local maxima were selected that exceeded the threshold providing a given false alarm probability, and then these maxima were combined. The upper limit of the false alarm probability with this processing method will be equal to

$$P_{fa} = P_{1fa} + P_{2fa} - 2P_{1fa}P_{2fa} \approx P_{1fa} + P_{2fa}, \quad (5)$$

(this approximate equality is true for  $P_{1fa}, P_{2fa} \ll 1$ , which is usually satisfied) and it will be achieved in the absence of correlation between the background components of the images. Otherwise, the false alarm probability will be lower.

### 4 Numerical experiment

The increase in detection reliability is confirmed by a numerical experiment performed with multispectral images (size  $1024 \times 1024$ , spectral ranges: 1–0.45  $\div$  0.515, 2–0.525  $\div$  0.605, 3–0.63  $\div$  0.69, 4–0.775  $\div$  0.90 and 5–1.55  $\div$  1.75  $\mu\text{m}$ ) obtained by the Landsat 7 satellite [5]. In accordance with expression (1), small-sized objects with an average amplitude equal to 1.5 standard deviations (StD) of the background and uncorrelated noise with StD of 0.1 StD were additionally applied to the images pair of different spectral ranges. Object detection was carried out after filtering the images by adaptive filters, implemented according to (3) and (4), by thresholding, which provides a given false alarm probability  $P_{fa}$ . The first detection option consisted of selecting a threshold separately for each image and combining points that exceeded the threshold into one image. The second was to select a threshold and detect points that exceeded the threshold in the sum of the filtered images. Next, the detection probabilities in each image (**P1** and **P2**), in the summarized image **P $\Sigma$** , and the detecting probability **Por** obtained as a result of combining the points selected in each image were estimated.

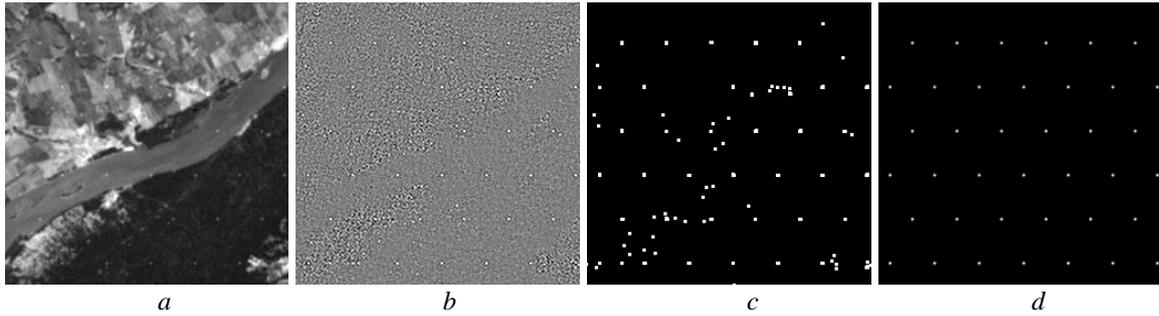
The processing results for a given false alarm probability  $P_{fa} = 0.005$  are illustrated in the table below. The column **R** of the table shows the correlation coefficients between the images in the selected channels, and the columns **Kn** show the ratio of the standard deviation of residual noise (background + noise after filtering) to the standard deviation of noise in the original image. These numbers show that the use of a locally stationary model can reduce the average background level to a value comparable to the noise level in the original images. In parentheses in columns **P1** and **P2** are given the detection probabilities for  $P_{1fa} = P_{2fa} = P_{fa}/2$ , which, when combined according to (5), provides an upper limit of the false alarm probability equal to  $P_{fa}$ .

It follows from the table, first, that image filtering, based on the formation of a local background model, reduces the background component standard deviation to a value comparable to the noise standard deviation. Secondly, the images joint processing of different spectral ranges reduces the false alarm probability. Thirdly, the smaller the cross-correlation between the background component of the images, the less likely the false alarm.. Fourth, with a fixed false alarm probability, joint processing increases the detecting probability objects. Figures 1,2 illustrate the process and of a two-color image joint processing result at  $P_{fa} = 0.005$  (fragments of images with a size of  $256 \times 256$  pixels are shown).

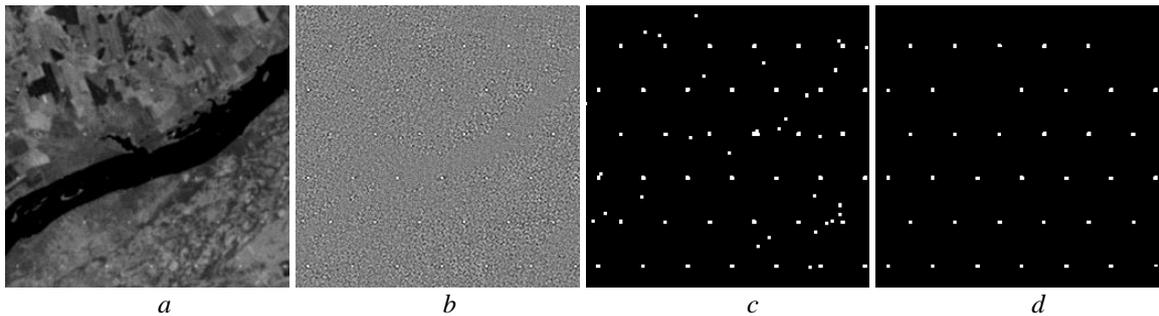
**Table.** Joint processing of different spectral ranges image pairs results

Channels	R	$P_{fa}$	P1	Kn1	P2	Kn2	Por	$P\Sigma$	Kn $\Sigma$
1-2	0.91	0.005	0.95(0.88)	1.69	0.89(0.80)	1.81	0.95	0.96	1.48
1-3	0.92	0.005	0.95(0.88)	1.69	0.92(0.85)	1.76	0.95	0.98	1.48
1-4	-0.49	0.005	0.95(0.88)	1.69	0.99(0.97)	1.56	1.00	1.00	1.05
1-5	0.45	0.005	0.95(0.88)	1.69	1.00(0.99)	1.46	1.00	0.99	1.28
2-3	0.85	0.005	0.89(0.80)	1.81	0.92(0.85)	1.76	0.93	0.94	1.51
2-4	-0.22	0.005	0.89(0.80)	1.81	0.99(0.97)	1.56	1.00	1.00	1.16
2-5	0.47	0.005	0.89(0.80)	1.81	1.00(0.99)	1.46	0.99	0.99	1.33
3-4	-0.42	0.005	0.92(0.85)	1.76	0.99(0.97)	1.56	1.00	1.00	1.06
3-5	0.65	0.005	0.92(0.85)	1.76	1.00(0.99)	1.46	0.99	0.99	1.32
4-5	0.25	0.005	0.99(0.97)	1.56	1.00(0.99)	1.46	1.00	1.00	1.04

In Figures 1,2 images with indexes  $a$  are fragments of 3-rd ( $0.63 \div 0.69 \mu\text{m}$ ) and 4-th ( $0.775 \div 0.90 \mu\text{m}$ ) channels of source multispectral image with added small objects (figure 1, $d$ ). Objects size is determined by recording device point spread function and approximately equal to  $1.5 \div 2$  pixels. Images with indexes  $b$  in both figures are obtained after adaptive filtering images  $a$ , implemented according to (3) and (4), and with indexes  $c$  – after thresholding with level, determined by  $P_{fa} = 0.005$ . Figure 2,  $d$  shows objects, detected after conjunction marks of figures 1,  $c$  and 2,  $c$ .



**Figure 1.** Two-color images joint processing (a-c: channel 3).



**Figure 2.** Two-color image joint processing (a-c: channel 4)

## 4 Conclusion

The proposed method for approximating a spatially unsteady background by a locally stationary model based on an optimal linear prediction reduces the background level in images containing small sized low-contrast objects to a value comparable to the noise level. Subsequent detected signals joint processing in different channels of a two-color image allows, with a fixed false alarm probability, to increase the objects detection probability.

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## References

- [1] Kirichuk V.S., Pustovskikh A.I. Using Statistical Methods for Stationary Part of Background Estimation in Image Series // *Avtometriya*, 1988, No. 3, pp 74-78 (in Russian).
- [2] Tartakovsky A.G., Brown A.P., Brown J. Nonstationary EO/IR Clutter Suppression and Dim Object Tracking // *Proceedings of the 2010 Advanced Maui Optical and Space Surveillance Technologies (AMOS) Conference*, Maui, Hawaii, September 14–17, 2010.
- [3] Gromilin G.I., Kosykh V.P., Popov S.A., Streltsov V.A. Suppression of the Background with Drastic Brightness Jumps in a Sequence of Images of Dynamic Small-Size Objects // *Optoelectronics, Instrumentation and Data Processing*, 2019, Vol. 55, No. 3, pp. 213–221.
- [4] Andersen T.W. *The Statistical Analysis of Time Series*. Wiley, New-York, 2011, 358 p.
- [5] Global Land Cover Facility. <http://glcf.umiacf.umd>