# Small-Size Target's Automatic Detection in Multispectral Image using Equivalence Principle

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***Abstract*****—**The task of compact small-size target's automatic detection in multispectral satellite image is discussed. A new method for the probability of correct target detection in multispectral image taking into account both spectral and spatial features is proposed. The method is based on using the equivalence principle in terms of equivalent signal-to-noise ratio in multispectral imagery. Theoretical estimates and practical results on performance comparison of the ships detection on sea surface by proposed method and using traditional approach are presented.

***Keywords*****—** automatic target detection, multispectral image, spectral features, target detection probability.

## I. INTRODUCTION

Continuous technical development of space-borne electro-optic imagers has resulted in almost complete evolution to multispectral and hyperspectral technologies for remotely sensed image registration [1].

Remote sensing applications necessarily involve detection of various objects, characterization of their qualitative features and quantitative specifications, creation of maps of their spatial distribution, multifarious scientific, managerial or special-purpose decision making based on the conducted analysis results.

A special interest in remote sensing applications is the information systems development intended to store, process and analyze huge volumes of data coming from satellite and airborne Earth observation platforms. The operation of such systems definitely needs a near-real-time automatic target detection in images.

The main features of objects recognition in panchromatic high-resolution images are spatial features. These features include, first of all, the size, shape and other geometric properties of the object, which are easily interpreted by human vision, enhanced by modern software for image processing and analysis support [2].

Direct extraction of total information from multispectral images by human is impossible, because the human visual perception cannot support parallel vision of more than three data layers [3], [4]. In this case, the recognition of observed object is made using spectral features, which based on not structural analysis, as in the case of recognition by spatial features, but correlation one, more suitable for the implementation of automatic target detection, although it requires knowledge of the observation conditions, especially the illumination, and background parameters [5], [6].

As a result of multispectral imaging, a multi-dimensional spatial-spectral image is formed in which each image pixel is characterized by its own discretely represented spectrum called as spectral signature. If insufficient spatial resolution of imager, then target detection is fulfilled by spectral features only. The target's spectral pattern is extracted from one or several pixels, and the pixel-wise scanning of whole image is performed for target detection [7].

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So, a catalogue of targets spectral signature data, namely a database containing the spectral reflectance of various natural and man-made objects is needed for the targets detection by their spectral features [8].

The contradiction in the spatial target detection by its multidimensional spectral description can be solved using the equivalence principle, which means a statistical convolution of multidimensional spectral signatures of multispectral image into an one-dimensional statistical value – the probability of correct target recognition, which is a detection performance quantity [9].

The increase in multispectral data streams when surveying large areas – on the one hand, and the impossibility of use or limited capacity of target's spatial features, common for the visual interpretation – on the other hand, results in unavoidable automatic detection of specified spectral signatures within the spatial-spectral data cube [10].

For this reason, the development of efficient method for the target's automatic detection in multispectral images using spectral features is a highly topical problem now.

## II. STATE OF THE ART

The multidimensional optical signals, which are specified as random sequences of radiometric values depending on the optical wavelength $\lambda$, must be analyzed for target's automatic detection in multispectral image. In such representation, the spectral features of the optical signal are discrete random process' parameters. Since radiometric features altered in different spectral bands, the corresponding random process should be considered as non-stationary. To guarantee statistically stable separation of multidimensional optical signals, it is necessary to postulate that the basic statistical parameters of random processes that describe the same object within at least one multispectral image are constant [11].

Most of the multispectral image analysis methods are based on advanced, but not principal, general-purpose methods for multidimensional data analysis. Such methods are usually based on comparing the spectra of individual pixels in a multispectral image with the target spectra taken from the reference spectra catalogue [12].

Comparative spectra analysis is implemented by algorithms of automatic or supervised classification using different spectral similarity metrics, primarily statistical [13]-[15]. The main methods for multispectral images classification are: the minimum distance (MD) method – assigns the classified pixel to a class which center is at the minimum Euclidean distance in the multidimensional feature space [16]; spectral angle mapper (SAM) – identifies the class closest in angle to the vector of the classified pixel [17]; support vector machine (SVM) – builds a class-separating surface in the spectral coordinate space [18]; Mahalanobis distance (MahD) and maximum likelihood (ML) classifiers–restores the classes probability density distributions in the spectral space [19].

The main disadvantage of the mentioned methods for multispectral imagery analysis is that one's do not represent relations between radiometric signals of objects and probability of their correct detection.

Another disadvantage of the mentioned methods is the non-regarding of objects mutual location on the land surface, i.e. spatial properties of objects. Usually spatial properties are determined by several pixels inside a pre-specified vicinity.

A common feature of all considered methods is the statistical nature of multidimensional data analysis for object detection in multispectral image [20]. For this reason, the target detection probability is the main performance measure of multispectral data analysis [21].

In this context, the approach to automatic object detection can be useful and constructive. Such approach may be based on calculation of spectral signatures' correct recognition probability in multispectral satellite images taking into account the imager's radiometric specifications, observed backgrounds, equivalent spatial resolution of multispectral imagery [22], and perhaps spatial features of objects on the land surface.

## III. MATERIALS AND METHODS

The main specifications of multispectral imagery, which determine the possibilities of one's correct interpretation, are spatial resolution and radiometric properties. Whereas the spatial resolution consequence has been investigated for several decades and modeled quite correctly [23], the radiometric properties are taken into account mainly through radiometric contrast [24], which is reasonable for panchromatic satellite images and incorrect for multispectral ones [25].

Currently, many approaches have been developed to evaluate the possibilities of correct interpretation of multispectral imagery. A wide range of models are used for this purpose, for example, based on Johnson's criterion [26], on various semi-empirical relationships [27], on the Bayesian fusion of partial probabilities [28], and so on. The main disadvantage of most available approaches is the unsuitability to multispectral imagery analysis with spatial resolution allowance. Therefore, fully automatic detection of small-size targets in satellite multispectral images is possible only by spectral, as a rule, statistically defined features [29].

The problem of target detecting in multispectral image reduces to estimating the probability of the target's spectral signature presence in the combined spectral signature of each image pixel. In that event, the target's reference spectral signature is considered as the useful signal, and the particular pixel's signature in the multispectral image is considered as an additive mixture of signal and background. The applied spatial-statistical model allows to estimate the probability of the given signature presence in the current pixel [30]. Here the signal-to-noise ratio becomes the key parameter of detection.

Both spatial resolution and signal-to-noise ratio determining procedures are sufficiently developed and are not difficult for one-dimensional panchromatic or one-band images, but these values are undefined for multispectral imagery. It is possible to resolve such uncertainty for multispectral imagery using the equivalence principle [31]. This requires the multidimensional statistical methods engagement, in particular the Bhattacharyya statistical metric [32].

For small-size targets detection in multispectral images the probability $P_0$ of correct detection of the given spectral signature is estimated as [33]:

$$P_0 = \exp\left[\frac{2\sqrt{2}\,\ln\alpha\cdot\mathrm{erf}^{-1}(2\alpha-1)}{\psi}\left(\frac{d}{d_0}\right)^2\right] \tag{1}$$

where $\psi$ is the equivalent signal-to-noise ratio in multispectral image, $d$ is the spatial resolution on the ground, $d_0$ is the characteristic detail of the target, i.e. detail required for reliable target detection, $\alpha$ is the confidence level when a spatial resolution is equal to characteristic detail and radiometric modulation is sufficiently high. An equivalent signal-to-noise ratio in a multispectral image can be evaluated as [34]:

$$\psi \cong \mathrm{erf}^{-1}(1-2e^{-B}) \tag{2}$$

where $B = -\ln\sum\sqrt{f(\rho_0)\cdot f(\rho)}$ is the Bhattacharya statistical distance, $f(\rho_0), f(\rho)$ are the probability densities of statistical distributions of target and background multidimensional spectral signatures $\rho_0$ and $\rho$.

Equation (1) calculates the probability of correct detection of target's spectral signature in multispectral satellite image, and since in general the equivalent signal-to-noise ratio in multispectral image is greater than in panchromatic or color-synthesized one [35], consequently this probability is expected to be higher.

Theoretical evaluations, visualized by the Fig. 1 plot, show the exceedance of probability $P$ of correct target's detection in multispectral image with the equivalent signal-to-noise ratio over the traditional method, which uses the maximum one-band contrast [36]. The abscissa axis plots the imager spatial resolution, normalized to the characteristic detail of the target.

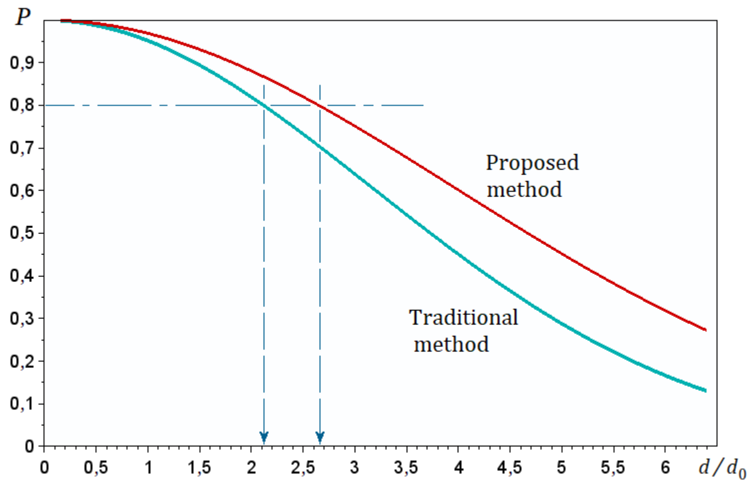


Fig. 1 Dependence of the detection probability of a given spectral signature on the relative spatial resolution of multispectral imager

Under constant relative spatial resolution $(d/d_0)$, the main informative parameter in (1) is the equivalent signal-to-noise ratio $\psi$, depending on Bhattacharyya's distance $B$. The general nature of this relationship is illustrated in Fig. 2.

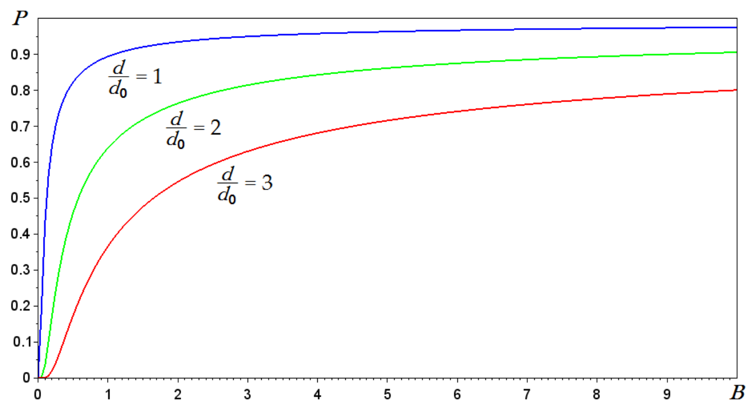


Fig. 2 Dependence of the detection probability of a given spectral signature on the Bhattacharya's statistical distance to the background

Incorporating the equivalent signal-to-noise ratio ψ into equation (1) opens the possibility not only to make a more reasonable estimation of the probability of small-size targets' detection in multispectral satellite image, but also to actually enhance it through use an additional information contained in multispectral image as compared with any single spectral band [37].

## IV. RESULTS AND DISCUSSION

Practical verification of the proposed method was performed by detecting small-size targets (sea ships) in the Sentinel-2 multispectral satellite image, displayed in Fig. 3.

Fig. 3 Natural color-synthesized Sentinel-2 multispectral satellite image fragment (L2A, 23.07.2019, 10 spectral bands, 10 m ground spatial resolution)

A special kind of object-oriented image analysis (OBIA) [38] has been used to neutralize possible inter-pixel targets locations in the image. For this purpose, the equivalent signal-to-noise ratio is estimated not only in the current pixel but also in adjacent pixels spatially connected with it. The hypothesis about full signal reallocation between the current pixel and one of the adjacent one is tested. Then the full signal-to-noise ratio ψ is decomposed as:

$$\psi = \psi_0 + \triangle \psi \quad (3)$$

where $\psi_0$ is the equivalent signal-to-noise ratio in the current pixel, $\triangle \psi$ is a some additional increment caused by the subpixel part of target located in adjacent pixel.

Obviously, the $\triangle \psi$ value in (3) cannot exceed $\psi_0/2$ and will depend on the target's spatial displacement, so its quantity under consideration should be limited to the threshold $\psi^*$, which can be determined for geometric reasons:

$$\triangle \psi \leq \psi^* \quad (4)$$

A comparison was carried out between the results of the ships detection in multispectral satellite image of Fig. 3 using both developed method and a commonly used support vector machine one, which usually reach a quite high efficiency in target detecting by spectral features [39].

The results of ships detection over the sea surface background in the Sentinel-2 multispectral image by the proposed method are shown in the Fig. 4, and by the SVM – are in Fig. 5.

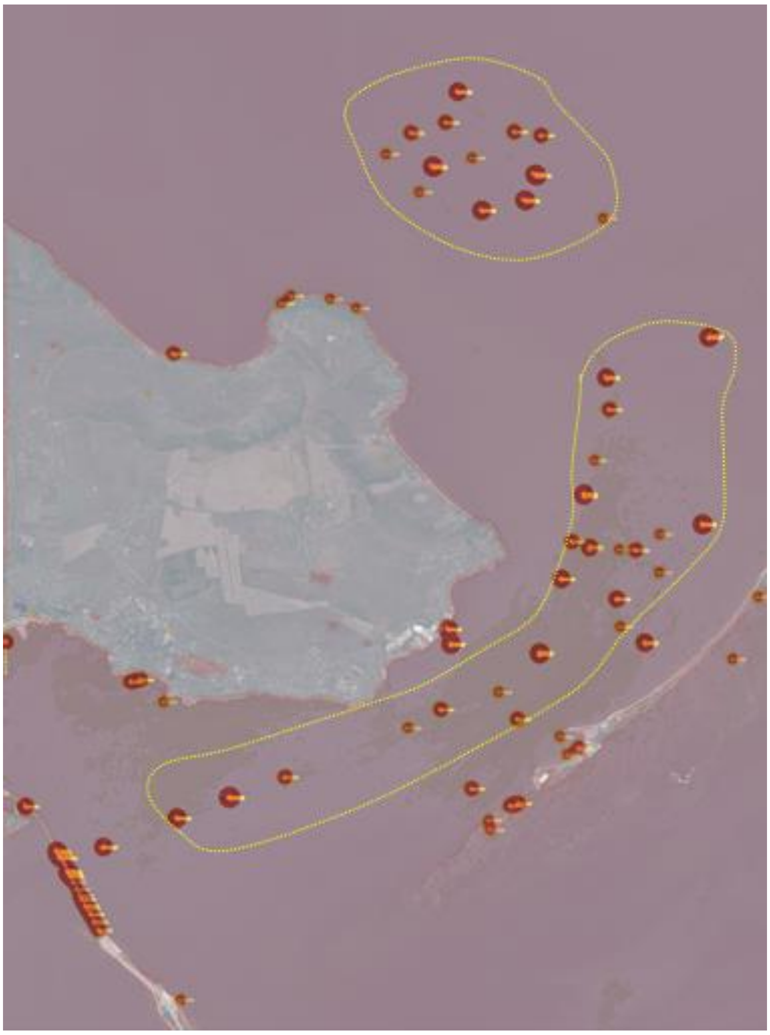

Fig. 4 The Sentinel-2 input image fragment with results of ships detection by spectral features using the developed method

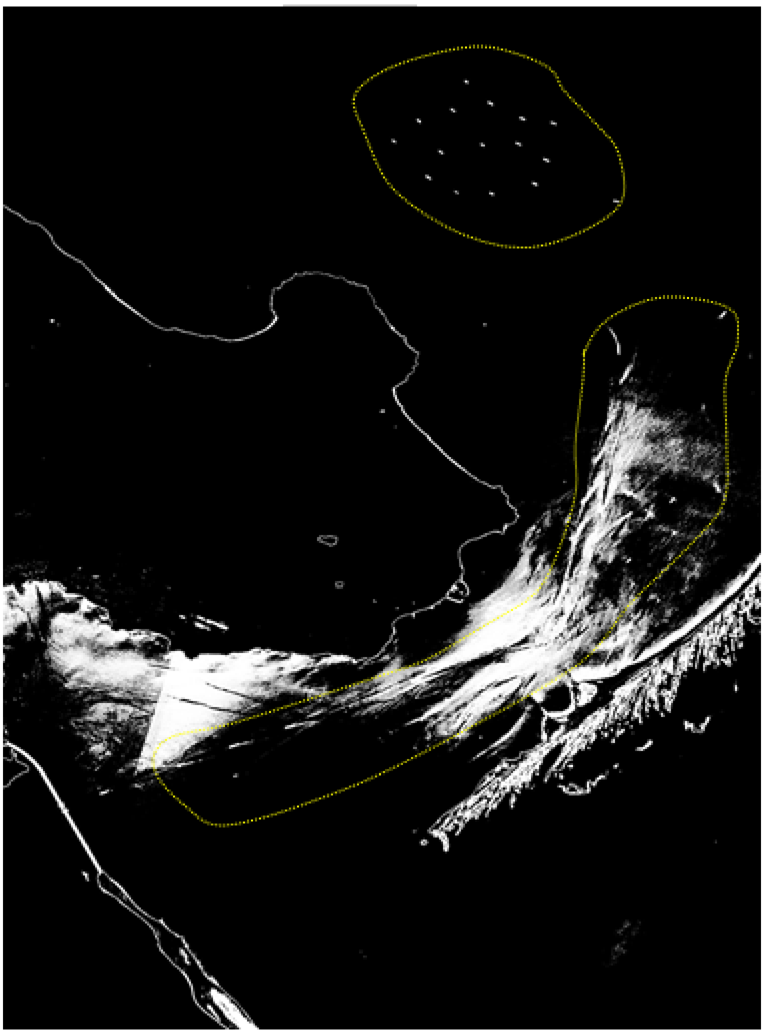

Fig. 5 The Sentinel-2 input image fragment with results of ships detection by spectral features using SVM

Target detection efficiency was rated over test sample, by matching results obtained and visual detection data acquired from high-resolution image. The targets detection rate under the predefined probability threshold was used as reliability criterion. It was calculated as a quotient of the number of correctly detected targets and the total number of targets actually existing in the image.

An analysis of results obtained shows that the over-threshold probability (assumed to be greater than or equal 0.8) area mapped by the developed method is more accurate corresponds to existing targets. Targets on the sea surface are clearly distinguishable in Fig. 4, while in Fig. 5 target segments are rather noisy. Furthermore, there are large number of false detections in Fig. 5, e.g. corresponding to land segments. The false detections are much more rare when the proposed method was applied.

Quantitative results of the considered methods comparison are given in Table 1.

TABLE I
TARGET DETECTION COMPARISON RESULTS

| Method used for targets detecting | Number of targets: correctly detected / total | Percentage of correctly detected targets |
|---|---|---|
| Method based on the equivalence principle | 36 / 46 | 78.2 |
| SVM method | 18 / 46 | 39.1 |

Table 1 shows that the use of proposed method (based on the equivalence principle) enhances the small-size targets' detection performance in multispectral image by 39 % versus the SVM method.

## V. CONCLUSIONS

An advanced method for small-size target's detection in multispectral image is proposed. The method is based on the equivalence principle, which reduced multidimensional spectral data down to a one-dimensional distribution of detection probability. The method takes into account both spectral (in the form of an equivalent signal-to-noise ratio) and spatial (via the sensor resolution as well as the OBIA elements) target's features.

The paper describes example of small-size targets – sea ships detecting in the 10 m spatial resolution Sentinel-2 multispectral image using both the developed method and the well-known SVM one, which is quite credible and proper for this task. A comparison of the achieved reliability of small-size targets detecting demonstrates an essential advantage of the developed method coincidently with a significantly lower number of false detections.

The future researches should be focused on creation and updating the comprehensive spectral library required for practical applications of the proposed method, on algorithms improvements for targets' spatial features handling, as well as on software development for the multispectral satellites imagery analysis based on the proposed method.

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