Model for selecting the Earth observation satellite systems by object recognition probability

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The paper provides a model for selecting satellite systems for optical observation of the Earth by the probability of recognizing objects. The model is based on improved rules for selecting satellites by the spatial resolution of onboard imaging system. The model advantage over the known ones is the satellite systems selection not only due to the spatial resolution of image, but also taking into account the predictable contrast of objects and the required recognition level. The proposed model ensures a more correct pre-selection of satellite systems, in doing so reducing the cost of satellite imaging by preventing extra-requirements for spatial resolution of onboard imaging system. Also, the article proposes a method of forming a database of radiometric contrasts of typical objects and backgrounds for their consideration in the model for choosing satellite systems. This method does not depend on the specific types of on-board equipment, as well as on the availability of archival images at the time of planning satellite imagery.

Keywords: satellite system for optical observation, satellite image, spatial resolution, radiometric contrast, object recognition probability.

Introduction. Currently, geographical information systems (GIS) for various purposes are rapidly developing in the world. The primary source of GIS data is satellite imagery (SI), which is acquired from operators of satellite systems for optical observation (SSOO) \cite{1, 2}. To order SI, the corresponding online services are intended for SSOO selection based on the onboard imaging systems (OIS) specifications \cite{3}.

Due to the wide variety of available SSOO and significant differences in technical specifications of their OISs, the problem of automation of the SSOO selection becomes \cite{4}.

1. State-of-the-art

The main requirement for the OIS is to ensure the possibility of detecting, recognizing and classifying ground objects (GO), which primarily is depended on the provided spatial resolution \cite{5}.

Today, in the main known models, the required spatial resolution of SI is stated by a modified Johnson criterion, which was obtained experimentally and oftentimes was checked and updated \cite{6}.
It has a tabular form. The probability of correct SI interpretation $P_o$ depends on GO’s characteristic detail $d_o$. In turn, the characteristic detail is determined by number of resolving elements $n^P$ in the linear size $l_o$ of GO:

$$d_o = l_o / n^P$$

The $n^P$ value is more or less constant for all simple GO. Traditionally it is defined for the interpretation probability $P = 0.5$ [7] and is designated as $n^P=50\%$ (Table 1).

| Table 1 | Value of Johnson criterion for GO interpretation |
|---------|-----------------------------------------------|
| Criterion value | Quantity of resolving elements required for appropriate level of interpretation |
| $n^P=50\%$ | detection | classification | recognition | identification | intent determination |
| $2.0 \pm 0.5$ | $2.8 \pm 0.7$ | $8.0 \pm 1.6$ | $12.8 \pm 3.0$ | $33.3 \pm 6.5$ |

If it is necessary to determine $n^P$ for probability $P \neq 0.5$, then adjusting factor $m$ must be applied:

$$n^P = mn^P=50\%$$

where $m$ depends on the required probability and is specified according to Table 2.

| Table 2 | The adjusting factors for Johnson criterion |
|---------|-----------------------------------------------|
| $P$ | 0.00 | 0.02 | 0.10 | 0.30 | 0.50 | 0.80 | 0.95 | 1.00 |
| $M$ | 0.00 | 0.25 | 0.50 | 0.75 | 1.00 | 1.50 | 2.00 | 3.00 |

So, for determination of GO characteristic detail $d_o$, it is necessary to know its linear size $l_o$ and the set the required probability $P$ of SI interpretation. Then the satellites equipped with OIS provides spatial resolution $d_s \approx d_o$ or equivalent, the acquired SI with $d_i \approx d_o$ resolution, can be chosen as suitable by spatial resolution.

At the same time the $d_s$ and $d_i$ parameters are unambiguously related by dependence

$$d_i = f(d_s, \Delta)$$

where $\Delta$ are parameters which are determined by OIS features and imaging conditions. In particular, the dependence (3) can be set in an explicit form [8] as

$$d_i = \zeta d_s$$

where $\zeta$ is a proportionality factor which considers the actual resolution degrading owing to optical signal distortion in the SSOO[9]. This factor can be estimated using the modulation transfer function (MTF) of the SSOO imaging model [10].

Classical approach to estimate spatial resolution defines one as maximum spatial frequency of a periodic test chart, consisting of black and white bars. Spatial resolution is estimated over an absolute contrast chart by the system’s MTF. For digital SSOO the spatial resolution can be estimated over sharp (high-contrast) edges in image using statistical technique [11]. As the object’s recognition probability depends not only on spatial resolution, but also on radiometric contrast, the resolution value (as well as a
characteristic detail) is determined as a rule for high contrasts [12]. Therefore in many scenarios image providers and users consider $\zeta \approx 1$ that causes the $d_i \approx d_s$ equality.

Taking into account the abovementioned, now the suitable SSOO selection is carried out by simple two-level rule [13]:

$$\mathcal{R}(d_s) = \begin{cases} \mathcal{R}^+ & \text{if } d_s \leq d_o \\ \mathcal{R}^- & \text{if } d_s > d_o \end{cases}$$

(5)

where $d_s = d_i \vee d_s$ is the generalized spatial resolution of SSOO, $\mathcal{R}^+$ and $\mathcal{R}^-$ are positive (selected) and negative (non-selected) solutions respectively. It is possible to achieve the $d_i$ value from SI providers and $d_s$ one – from OIS technical specifications. The three-level rule is more accurate:

$$\mathcal{R}'(d_s) = \begin{cases} \mathcal{R}^+ & \text{if } d_s << d_o \\ \mathcal{R}^0 & \text{if } d_s \approx d_o \\ \mathcal{R}^- & \text{if } d_s >> d_o \end{cases}$$

(6)

where $\mathcal{R}^0$ is the provisional solution which can become positive or negative after considering the additional information (external conditions, an imaging mode, OIS performance and so on). The main drawback of the considered approach is that in operational practice usually $d_i \neq d_s$, and objects’ contrasts are low. Then the SI recognition probability differs from expected one. So, the rules (5) and (6) are needed to be improved. Hence, the aim of paper is technique development for the SSOO selection by GO recognition probability.

2. Materials and methods

Recent studies show that the probability of the GO recognition in SI strongly depends on the radiometric (brightness) contrast [14]. Therefore the radiometric contrast of objects over corresponding background must be considered when selecting the SSOO by SI resolution.

2.1. Satellite systems selection model. The contrast $K_o$ characterizes relative exceeding of brightness of GO over background brightness [15]:

$$K_o = \frac{|B_o - B|}{B_o + B}$$

(7)

where $B_o$ and $B$ are brightness’s of object and background respectively.

The radiometric contrast’s (7) influence on the GO recognition probability is described by equation:

$$d_s = \frac{\ln P}{\ln \alpha} \frac{1 + K_o \cos \gamma}{1 - K_o}$$

(8)
where $\alpha$ is confidence level (usually accept $\alpha = 0.95$) [16], $\gamma$ is the OIS sighting angle relative to nadir. If notating

$$
\zeta(P, K_o, \gamma) = \sqrt{\frac{\ln P}{\ln \alpha} \frac{1 + K_o}{1 - K_o} \cos \gamma}
$$

(9)

then

$$
d_* = d_o \zeta(P, K_o, \gamma)
$$

(10)

becomes relation between the objects characteristic detail $d_o$ and spatial resolution $d_*$ for required recognition probability $P$.

Fig. 1 diagram shows dependence between the OIS relative spatial resolution $d_* / d_o$ and radiometric contrast $K_o$ using traditional ($d_* \approx d_o$) and updated ($d_* \neq d_o$) criteria in nadir imaging case ($\gamma \approx 0^\circ$).

![Figure 1](image)

Figure 1 – Dependence between the relative spatial resolution and radiometric contrast of GO under probability $P$ constraint

Based upon Fig. 1 in a $d_* / d_o > 1$ case for high contrast it is possible to weaken requirements to OIS spatial resolution and by that to expand a range of suitable satellites. For example, at $K_o = 0.8$ and $P = 0.8$ it is enough the SI resolution $d_* \approx 2d_o$, that is it is twice worse than the GO’s characteristic detail. On the contrary, at $d_* / d_o < 1$ for small contrast the required recognition probability cannot be achieved even at $d_* \approx d_o$, which results in mission unaccomplishing [17]. For example, at $K_o = 0.08$ and $P = 0.8$ it is necessary the SI resolution $d_* \approx 0.55d_o$, that is almost twice the best than GO’s characteristic detail.
On the basis of above stated the updated two-level rule is offered for SSOO selection

\[
\mathcal{R}(d_*) = \begin{cases} 
\mathcal{R}^+ & \text{if } d_* \leq d_o \varsigma(P, K_o, \gamma) \\
\mathcal{R}^- & \text{if } d_* > d_o \varsigma(P, K_o, \gamma)
\end{cases}
\] (11)

as well as the updated three-level one:

\[
\mathcal{R}'(d_*) = \begin{cases} 
\mathcal{R}^+ & \text{if } d_* << d_o \varsigma(P, K_o, \gamma) \\
\mathcal{R}^0 & \text{if } d_* \approx d_o \varsigma(P, K_o, \gamma) \\
\mathcal{R}^- & \text{if } d_* >> d_o \varsigma(P, K_o, \gamma)
\end{cases}
\] (12)

The primary advantage of the proposed rules (11) and (12) over known ones (5) and (6) is that the suitable SSOOs are selected not only by OIS resolution, but additionally taking into account pre-estimated contrast of GO and required recognition probability. It is significantly expands the range of suitable satellites.

For implementation of the offered way it is necessary to have the corresponding database (\(D\)) of radiometric contrasts of standard GO on backgrounds of the area of observation.

2.2. Radiometric contrasts database creation. As follows from (10), it is necessary to create and to update periodically a radiometric contrasts database for typical objects and backgrounds over the area of observation.

At the first stages of database creation the direct measurements of GO radiometric contrasts over actual backgrounds by a photometry of archive SI are used. A drawback of such approach is non-universality, i.e. inapplicable to objects and backgrounds missing in SI as well as the dependence on the specific OIS types. The acquisition of precision spectral reflectance of typical natural and man-made objects and covers is more adequate. Afterwards, such database integration into the geographic information system (GIS) is desirable.

Proposed approach allow to avoid of mentioned drawback, but demands radiometric conversion of spectral reflectance into the corresponding values of SI. If the GO surface irradiance from the Sun is \(E_o(\lambda)\) then the spectral radiance \(B_o\) of the OIS registered radiation is [18]

\[
B_o = \frac{1}{\pi} \int E_o(\lambda) \rho_o(\lambda) \tau(\lambda) S(\lambda) d\lambda
\] (13)

where \(\rho_o(\lambda)\) is the GO’s spectral reflectance, \(\tau(\lambda)\) is the atmosphere’s spectral transmittance, \(S(\lambda)\) is the OIS’s spectral response.

The solar spectral irradiance \(E_o(\lambda)\) can be calculated according to the E-490-00 [19] standard, the \(S(\lambda)\) spectral response is provided within OIS technical specifications, and atmosphere’s transmittance can be evaluated by any of the known methods for atmospheric correction [20]. Radiometric contrast values are calculated for the list of typical GOs by the destined OIS specifications (Fig. 2).
The satellite imaging simulation is performed by means of special-purpose GIS. The simulation output is a set of the area swaths. The spectral reflectances of GOs and backgrounds are extracted from spectral reflectance database for area swaths. Next, the radiometric conversions (13) are carried out over the extracted spectral reflectances. Finally, the radiometric contrasts values are calculated by (7).

2.3. Algorithm for selecting the SSOO by GO recognition probability. The procedure of the SSOO selection by the GO recognition probability is explained in Fig. 3 flowchart.
Input data of algorithm is the characteristic detail $d_0$ of GO, one’s radiometric contrast $K_0$, the OIS spatial resolution $d_s$ and the required probability of recognition $P$. The characteristic detail is assigned as minimum among all task-listed GOs. This ensures that all GOs will be recognized with a probability not less than the required one. The suitable SSOO selection is performed on the step 6 by updated criterion (11) or (12).

According to image interpretation practice, it is reasonable to set the required probability of GO recognition at 0.8 [21]. For the mission failure prevention the required probability can be reduced if none of the available SSOSs will not be suitable. At the same time, the 0.6 is the smallest permissible value of GO recognition probability.

The list $\{X_r\}$ of the selected SSOO, which are suitable by GO recognition probability taking into account both SI resolution and pre-estimated contrast of GO is the algorithm output.

3. Results and discussion

Developed model was applied to specific GO such as the large-size sea vessel (length is 181 m, width is 29 m, characteristic detail is 2.36 m), shown in Fig. 4. For a simple criterion (5) or (6), the SPOT-5 SSOO of 2.5 m spatial resolution is not suitable for this GO recognition, but for updated criterion (11) or (12), the SPOT-5 is quite suitable under condition of sufficient contrast.

At GO contrast at the level of 0.5 and OIS sighting angle of 30° the required spatial resolution (10) is equal 2.8 m and the probability of given GO recognition is equal to 0.84 (Fig. 4a). For comparison, the recognition probability of the same GO using the Pleiades-1 SSOO 0.7 m resolution satellite image is 0.99 (Fig. 4c).
Notwithstanding the excellent probability result, the Pleiades-1 imaging cost significantly increases (five times). The SPOT-5 SSOO also has a much larger swath width, and correspondingly, the revisit time. Therefore, it is quite reasonable to select it for such object recognition with an acceptable probability.

As other possible way to improve the GO recognition probability in satellite images is the resolution enhancement. Many methods for resolution enhancement are known, the single image super resolution (SISR) by means of artificial neural networks are especially popular among them [22]. The result of FSRCNN algorithm [23] applying to the SPOT-5 image is shown in Fig. 4b.

Conclusions. The paper provides a model for selecting satellite systems for optical observation of the Earth by the object recognition probability. This model significantly expands the possibilities and improves the quality of the choice of satellite systems through the use of a probability indicator of the correct recognition of objects in satellite images. The application of the proposed model can increase the efficiency and significantly reduce the cost of satellite imagery while ensuring the requirements for the reliability of information.

A feature of the algorithm that implements this model is, on the one hand, guaranteeing the correct recognition of given targets, and on the other hand, flexibility in relation to the required probability of their recognition. This advantage is achieved due to a more correct procedure for calculating the probability, in particular, by taking into account the expected radiometric contrast of the object. For the latter, a method is proposed for forming a database of radiometric contrasts of typical objects and backgrounds of the optical observation region.

The model described in the work is advisable to use in automated systems for planning satellite imagery to support decision-making on the use of a particular satellite system. The described automated decision support tools for the use of a particular satellite system can be integrated into industrial geographic information management systems.

It is advisable to carry out further research in the direction of developing methods for increasing the probability of recognition of objects. For example, through the use of the additional information which is contained in multispectral images and other data [24] or using one of the many known methods to increase the detail of a satellite image [25].

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Модель вибору супутникових систем оптико-електронного спостереження Землі за ймовірністю розпізнавання об’єктів

У статті подано модель вибору супутникових систем оптичного спостереження Землі за імовірністю розпізнавання об’єктів. Модель згрунтується на вдосконалених правилах вибору супутників за просторовою розрізненістю бортової знімальної апаратури. Перевагою моделі над відомими є вибір супутникових систем не лише за просторовою розрізненістю зображення, але і з урахуванням передбачуваного контрасту об’єктів та необхідного рівня розпізнавання. Запропонована модель забезпечує правильний відбір бортової апаратури, викріплює вартість супутникових знімків шляхом відбивання необхідності високої просторової розрізненості бортової апаратури. Також в статті пропонується метод формування бази данних радіометричних контрастів типових об’єктів і фонів для їх використання в моделі вибору супутникових систем. Цей метод не залежить від конкретних типів бортового обладнання, а також від наявності архівних знімків на час планування супутникової зйомки.

Отримано 25.04.20