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APPLICATION OF THE MODERN METHODS OF PROCESSING REMOTE SENSING DATA FOR SOLVING ECOLOGICAL PROBLEMS

Nowadays solution of different ecological problems, such as assessment of forests, water quality modeling, mapping of petroleum pollutions includes of an application of Remote Sensing (Figure 1). High resolution remote sensing hyperspectral images provide an important information about structure and details of objects. The procedure of hyperspectral image classification is a most important and difficult problem.

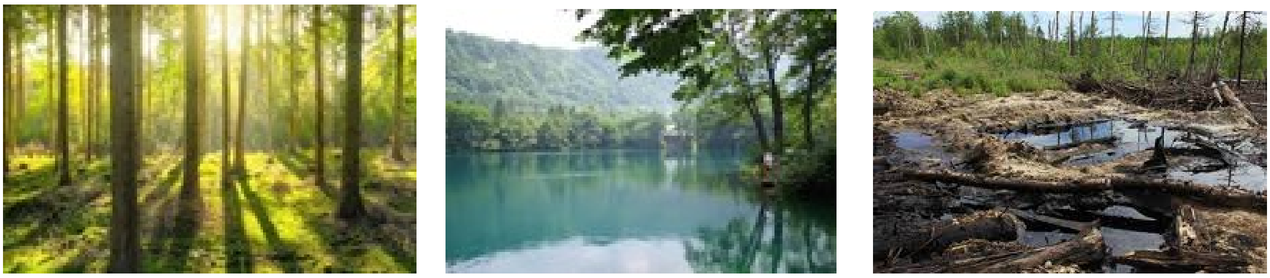

Fig. 1. Ecological tasks, that apply hyperspectral satellite images: assessment of forests, water quality modeling and petroleum pollutions

The main aim of this work is to consider the new hyperspectral image classification method, applying Normalized difference vegetation index (NDVI), Dempster-Shafer theory and Yager's combination rule. Consider the proposed classification algorithm using the following example. Suppose we have a territory on which the following classes are present: green vegetation, man-made objects, open soil, sand, roads, petroleum pollutions, water.

Our task is to determine the area with petroleum pollutions. Then we should identify and map these petroleum pollutions for conducting environmental monitoring of this studied area. The proposed method consists of two steps.

At the first step we apply NDVI and at the second step we apply main concepts of Dempster-Shafer theory and Yager's combination rule for mapping petroleum pollutions. Application of NDVI is the first step of classification procedure. At this step we can create mask based on NDVI and reduce the number of classes. This procedure reduces the volume of data and facilitates further calculations.

The NDVI is a dimensionless index, that describes the difference between visible and near-infrared reflectance of vegetation cover. Vegetation index can be used to estimate the density of green vegetation. NDVI will increase in proportion to vegetation growth [1-3].

The NDVI is calculated from these individual measurements as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED}, \quad (1)$$

where $NIR-$ spectral reflectance measurement acquired in the near-infrared region,

$RED-$ spectral reflectance measurement acquired in the red (visible) region.

The NDVI takes on values between -1 and 1.

Let's note, that different values of NDVI correspond to different classes of objects, such as: soil, water, roads, sand, green vegetation, petroleum pollutions.

If $NDVI = 1,$ we have an area with dense, healthy vegetation.

If $NDVI = 0,$ we have an area with nothing growing in it.

If $NDVI < 0,$ we have a lack of dry land.

Let's note, that NDVI takes on values between 0,2 and 0,8 for green vegetation, NDVI takes on values between -0,3 and 0,2 for man-made objects, open soil, sand, roads. If $NDVI < -0,3,$ we have water objects.

NDVI takes on values between -0,25 and 0,15 for *petroleum pollutions.*

Then we form a mask based on the calculated values of the NDVI for the original image. This procedure excludes from further analysis all areas on the image for which the values of the NDVI index are outside the range [-0.25; 0.15]. Applying this procedure we exclude areas of forest, grass, bushes and water bodies. Then remaining objects can be divided into a smaller number of classes: *petroleum pollutions,* buildings and roads, water.

At the second step we describe main concepts of Dempster-Shafer theory (generalization of probability theory) and Yager's combination rule for classification hyperspectral image.

In Dempster-Shafer theory, with every hypothesis A $(A \in 2^{\Omega})$ there is associated basic mass (basic probability assignment) $m(A)$ [3-5]. The $m(A)$ mass value represents the degree of belief allocated to the hypothesis *A*. This mass *m* belongs to the interval [0, 1].

Let's note, that mass *m* also satisfies the such conditions:

$$\sum_{A \subseteq 2^{\Omega}} m(A) = 1; \tag{2}$$

$$m(\varnothing) = 0.$$

Suppose the first source appointed to the hypothesis *A* a mass value m_1, and the second source independently appointed to the same hypothesis *A* a mass value m_2.

Yager's combination rule can can deal with highly conflicted information sources and process conflicting information [5-7]. Yager's combination rule assigns the masses of intersections of conflicting sets, which create an empty set in the intersection, to the base set. Non-null mass of the empty set is generally distributed among the elements of the frame of discernment.

Yager's combination rule is defined as:

$$m(A) = \sum_{B_1 \cap B_2 \cap \ldots \cap B_n = A} \prod_{1 \le i \le n} m_i(B_i), \;\; A \neq \varnothing, \; \theta, \tag{3}$$

where θ – set of hypotheses about membership of pixel (frame of discernment), 2^{θ} – total number of subsets of the θ, $m(\varnothing) = 0,$

$$m(\theta) = \sum_{B_1 \cap B_2 \cap \ldots \cap B_n = \theta} \prod_{1 \le i \le n} m_i(B_i) + K, \tag{4}$$

$$K = \sum_{B_1 \cap B_2 \cap \ldots \cap B_n = \varnothing} \prod_{1 \le i \le n} m_i(B_i). \tag{5}$$

The *K* is called the conflict coefficient. This coefficient reflects the degree of conflict among the sources. The range of values of the K lies within the interval [0, 1]. The more contradictions we have, the closer is the *K* value to 1. Zero value of conflict coefficient indicates the absence of contradictory assessments of the sources.

Consider an numerical example, where we determine the class of the pixel (object) π_n, applying basic probability assignments and Yager's combination rule. Suppose, that frame of discernment is $\theta = \{P, B, W\}$, where hypothesis P means, that sample belongs to class "Petroleum pollution", hypothesis B means, that sample belongs to class "Buildings and roads", hypothesis W means, that sample belongs to class "Water".

Suppose, we have two spectral bands. The sensors provide two bodies of evidence m_1 and m_2, respectively:

$$m_1(\{P\}) = 0,6; \;\; m_1(\{W\}) = 0,2; \;\; m_1(\{P, B\}) = 0,2.$$

$$m_2(\{W\}) = 0,1; \;\; m_2(\{P, B\}) = 0,5; \;\; m_1(\{P, W\}) = 0,4.$$

The combination *m* can be obtained, applying Table 1.

Table 1. Yager's combination rule

Basic probability assignment m_1 and m_2	$m_1(\{P\})$ 0,6	$m_1(\{W\})$ 0,2	$m_1(\{P,B\})$ 0,2
$m_2(\{W\})$ 0, 1	$\varnothing$ 0,06	$\{W\}$ 0,02	$\varnothing$ 0,02
$m_2(\{P,B\})$ 0,5	$\{P\}$ 0,3	$\varnothing$ 0,1	$\{P,B\}$ 0,1
$m_2(\{P,W\})$ 0,4	$\{P\}$ 0,24	$\{W\}$ 0,08	$\{P\}$ 0,08

Then we define basic probability assignments and determine maximum value of basic probability assignments:

$m(\{P\}) = 0,6 \cdot 0,5 + 0,6 \cdot 0,4 + 0,2 \cdot 0,4 = 0,62$ – basic probability assignment, that sample belongs to class "Petroleum pollutions";

$m(\{W\}) = 0,2 \cdot 0,1 + 0,2 \cdot 0,4 = 0,1$ – basic probability assignment, that that sample belongs to class "Water";

$m(\{P,B\}) = 0,2 \cdot 0,5 = 0,1$ – basic probability assignment, that sample belongs to the class "Petroleum pollution" or "Buildings and roads".

$$m(\{\varnothing\}) = 0,6 \cdot 0,1 + 0,2 \cdot 0,5 + 0,2 \cdot 0,1 = 0,18.$$

Applying Yager's combination rule, we can make conclusion, that sample belongs to class "Petroleum pollutions".

A new classification method, based on NDVI and Yager's combination rule was proposed in this work. It was shown, that this method consists of two steps. Application of NDVI is the first step of classification. It also was noted, that different values of NDVI correspond to different classes of objects. Analyzing different values of the NDVI, we can select special classes, that we need. After application of Vegetation Index Yager's combination rule can be used for further classification. Main advantages of this combination rule were described in this work.

It was noted, that Yager's combination rule can process incomplete and conflicting data. Yager's combination rule has the advantage of simple calculations too. It was considered an numerical example, where NDVI and Yager's combination rule were applied for detection and mapping of petroleum pollutions. Application of this new proposed classification method can be applied in ecological monitoring, assessment of forests, mapping of petroleum pollutions and other practical tasks [7-8].

References

1. Crippen R.E. Calculating the Vegetation Index Faster. Remote Sensing of Environment, 1990. Vol 34. P. 71-73.
2. Abidi M.A., Gonzalez R.C. Data Fusion in Robotics and Machine Intelligence. New York: Academic, 1992. P. 562-569.
3. Alpert S. A new approach to applying the discount rule in hyperspectral satellite image classification. Management of Development of Complex Systems, 2020. Vol. 43. P. 76-82.
4. Popov M., Alpert S., Podorvan V., Topolnytskyi M., Mieshkov S. Method of Hyperspectral Satellite Image Classification under Contaminated Training Samples Based on Dempster-Shafer's Paradigm. Central European Researchers Journal, 2015. Vol.1, № 1. P. 86-97.
5. Shafer G. A Mathematical Theory of Evidence. Princeton. NJ: Princeton University Press, 1976. P. 875-883.
6. Yager R. On the Dempster-Shafer Framework and New Combination Rules. Information Sciences, 1987. Vol. 41. P. 93-137.
7. Alpert S.I. A new band selection method for multispectral data based on criterion function of information capability. Management of Development of Complex Systems, 2023. Vol. 53. P. 23-29,
8. Alpert S.I. Data combination method in Remote Sensing tasks in case of conflicting information sources. Ukrainian Journal of Remote Sensing, 2021. № 8(3). P. 44-48.