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REMOTE SENSING OF ATMOSPHERE, HYDROSPHERE, AND UNDERLYING SURFACE

The Retrieval of the Coastal Water Depths from Data of Multi- and Hyperspectral Remote Sensing Imagery

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Abstract—A method is considered for rendering coastal water depths according to multi- and hyperspectral remote sensing imagery in the visible and near-infrared spectral regions. The depth is recovered for each pixel on the basis of solution of the inverse problem, which consists in artificial neural network learning with the use of a semianalytical model of radiation transfer in water, taking into account the effects of light scattering and absorption in the underwater light field, at least in three informative spectral channels for each bottom type. A possibility of adjusting the learning process is provided by the use of regression algorithms for determining organic and mineral impurities in water from their in-situ measurements. We enriched the library of the spectral characteristics of different bottom types and found informative identifiers for them. The results are tested on aircraft and hyperspectral space imagery data.

Keywords: bathymetry, hyperspectral data, reflectance, light absorption and scattering in water

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INTRODUCTION

Active development of the coastal sea areas and shelf zones during mining, dredging, and land reclamation leads to changes in the bottom relief, which requires periodical updating of information on the depths of the seas in coastal areas to ensure the safety of navigation. In the solution of this problem, Earth remote sensing means can be actively involved, because they allow receiving on-line information about the state of waters (in transparent ocean water at depths up to 20–25 m [1]) through measurements of upward radiation above the sea surface. The development of various technologies for receiving and processing hyperspectral (HS) imagery data, and the design of multispectral (MS) systems with many channels in the visible and near-IR spectral regions, present the possibility of on-line production of bathymetric maps with significantly lower costs as compared to traditional shipboard multi-beam echo sounders.

The known aerospace methods for the study of shelf depths use the empiric approach based on the analysis of images in two spectral regions: violet (400–450 nm) and yellow (580–620 m). This approach has certain disadvantages, conditioned by the possibility of monitoring only clear water and the need to obtain reference data on the depths for deriving a regression relation between the depth and reflectance for each bottom type.

The first data demonstrating the possibility of using these two spectral channels for assessing coastal waters were published by Lyzenga in 1978 and then developed by Stumpf [2, 3]. The method is reduced to the approximate estimate of depths in the violet region, where the effect of suspended mineral matter on the attenuation factor is absent, and in the yellow region, where the absorption by phytoplankton pigments is minimal.

Actually, the minimal coefficients of solar radiation attenuation by limnic components (dissolved and suspended organic matter, nonorganic salts, mineral suspensions, and so on) in transparent waters are observed in the spectral band 400–450 nm. The radiation flux at the wavelength $\lambda = 470$ nm in clear water can penetrate to depths of 10–20 m, while at $\lambda = 750$ nm it is almost totally attenuated in the layer 0.2–0.4 m [4]. At the same time, optical properties of the water column in the violet and blue spectral regions are strongly impacted by phytoplankton and dissolved organic matter, which significantly affect the light transmission, increasing the absorption in the short-wave spectral region. The maximal contribution of phytoplankton pigments to the blue absorption region is about 35% for highly productive sea and ocean waters [5]. Therefore, in the presence of phytoplankton, the depth should be estimated taking into account the chlorophyll concentration.

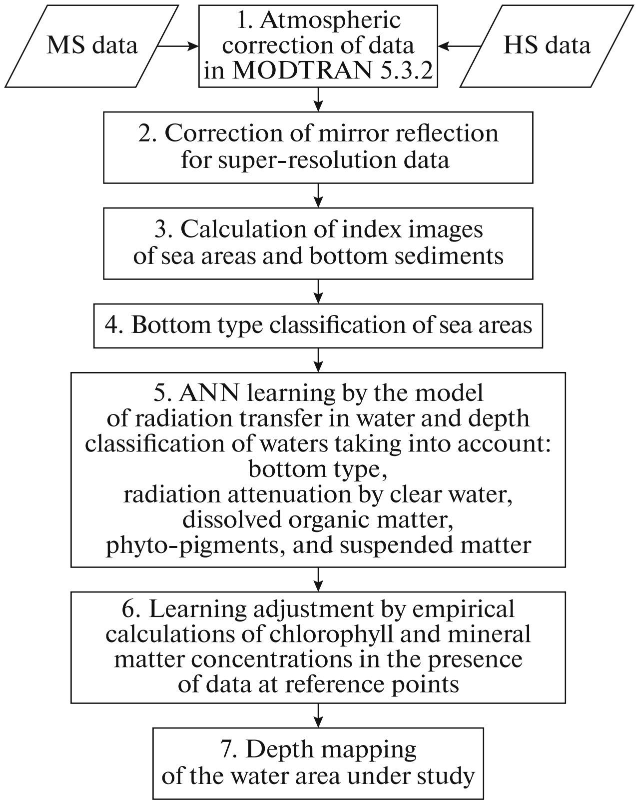

Fig. 1. Flow chart of the algorithm for estimation of depths of shelf sea zones from multi- and hyperspectral data.

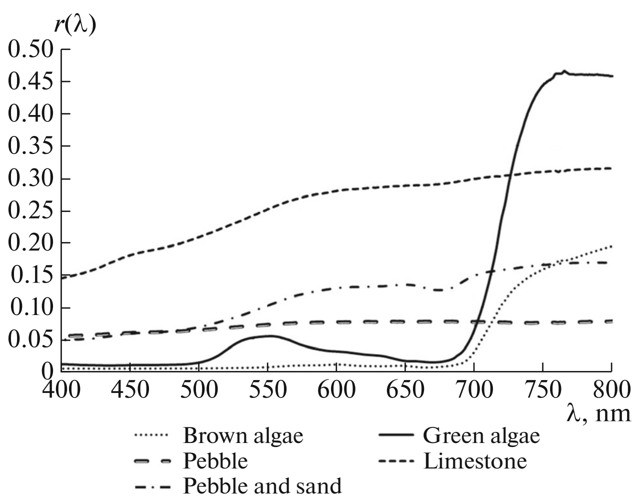

Fig. 2. Spectral brightness coefficients for various bottom types (open ground and algae) typical for the Black Sea.

These circumstances have led to the importance of developing the method for determining the depth of coastal waters, which is considered in this paper. The method is based on the use of a semianalytical algorithm for estimating the radiation transfer in sea water taking into account the influence of radiation attenuation in water and the contribution of the bottom albedo to the water surface brightness [4, 6]. The primary distinction of the method from the known analogues [2, 3] is the independence of the availability of initial data on depths at reference points, because the depth retrieval is performed through artificial neural network (ANN) learning using the equation of radiation transfer in water in the most informative spectral channels. In the learning, the backpropagation algorithm is used, which relates to the family of optimization methods, particularly to the method of gradient descent.

The generalized scheme of the technology used is shown in Fig. 1 and includes the following stages: preprocessing, including the atmospheric correction of data and correction of solar flashes; thematic processing, including bottom classification to two basic types (algae and ground), and retrieval of the depth of coastal sea areas. Below, we sequentially describe the methods used.

LEARNING AREA AND INPUT DATA

The experimental data on reflection characteristics of coastal seas were received and the suggested algorithm for depth estimation was tested using the results of test-flights above the Black Sea waters (near Sevastopol Bay, Kacha, and Koktebel) organized by Mozhaysky Military Space Academy.

During the experiments, the airborne video-spectrometer NPO "Lepton" (spectral resolution of 0.4–3 nm, spectral range 402–1031 nm) and the ground-based FieldSpec 3.0 spectroradiometer (spectral resolution of 3–10 nm, spectral range 350–2500 nm) were used. Together with data of aircraft and marine measurements, data from hyperspectral devices from the Russian spacecraft (SA) "Resurs-P" were used.

The FieldSpec 3.0 spectroradiometer was used for measurements of bottom spectral brightness coefficients $r(\lambda)$ in the shelf zone (Fig. 2), which were then used as input data for the algorithm, as well as spectral characteristics of shelf zones up to 3 m deep. From five to ten measurements were conducted for each zone; the $r(\lambda)$ confidence interval was within limits of 0.001–0.025 with a reliability of 0.95 and increasing with wavelength for algae.

MAIN PROCESSING STAGES

The first stage of the algorithm for depth estimation is the atmospheric correction of aerospace imagery data; it was performed using the MODTRAN 5.3.2 software for atmospheric radiation transfer simulation.

At the next stage of the processing, the bottom classification was performed using the following indices:

(1) $K_S = r_{570} - r_{480}$ for the open ground identification (sand, pebble);

(2) for the algae bottom, the wavelength value was used at which the gradient of the spectral characteristic was zero within 660–750 nm. In this range, the spectral signature of the bottom vegetation is characterized by a local brightness maximum at a wavelength

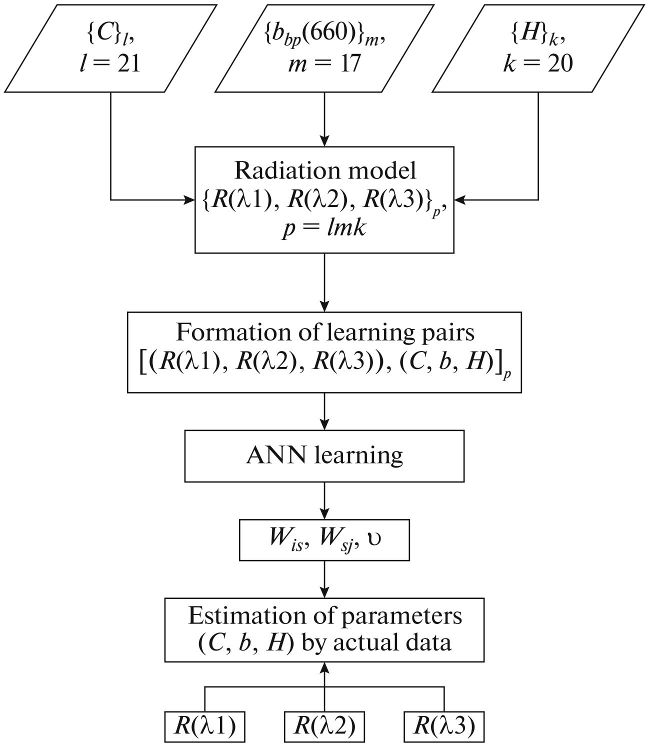

Fig. 3. Structural scheme of the use of ANN method for estimation of shelf sea area depths (l, m, and k are the number of variable values of C, $b_{bp}(660)$, and H, respectively; W_{is} are the weight coefficients between input and hidden layers of ANN; W_{sj} are the weight coefficients between the output and hidden layers of ANN; υ is the ANN learning time).

of about 710 nm (for brown algae) and 720 nm (for green algae).

Threshold values of the indices were found from values of the water depth reflectance calculated using a radiation model of light transfer through water and verified by experimental data. It was confirmed that the indices suggested, regardless of their variability versus hydro-optical properties of water, had a sufficient divisibility for their segmentation at depths of up to 4–5 m (at large depths, the bottom type weakly influences the water depth brightness). For example, threshold values of K_S for pebble in Sevastopol Bay were less than 0.015; for algae, less than 0.034; for pure sand (or limestone), between 0.016 and 0.08. In that case, it was important to choose the correct sequence of the classification algorithm by the decision tree method, in which algae areas were identified at the first stage, and only then the ground bottom types were classified in the remaining part of an image. All other sea areas, not meeting the threshold values of the indices, are related to deep water regions (deeper than 4–5 m).

Just after termination of the bottom classification, the depths of the sea areas under study are determined. The model of radiation transfer in the water column requires the parameters of radiation absorption and scattering in water, due to the presence of mineral and organic admixtures, probably unknown, to be set as input data. In turn, to solve the inverse problem and derive unknown parameters, including the depth, the authors suggest using multivariate optimization methods based on the preference of multivariate multi- and hyperspectral data. One of such methods is the algorithm of gradient descent, a version of which forms the basis for the backpropagation learning rule [7].

In this case, the model of radiation transfer in the water column [8]:

$$R_{dp}(\lambda)\left[1 - e^{-2fk_d(\lambda)H}\right] + R_b(\lambda)e^{-2fk_d(\lambda)H} = R_a(\lambda) \quad (1)$$

is used in the network learning. Here, $R_a(\lambda)$ is the sea spectral brightness coefficient; $R_b(\lambda)$ is the spectral value of the bottom albedo; $R_{dp}(\lambda)$ is the spectral coefficient of the water column diffuse reflection for an infinitely deep sea; $k_d(\lambda) = b_w(\lambda) + b_{bp}(\lambda) + a_w(\lambda) + a_{ph}(\lambda)$ is the spectral index of radiation vertical attenuation (forward and back), m^{-1}; $a_w(\lambda)$ and $b_w(\lambda)$ are the known coefficients of absorption and backscattering by clear sea water [5]; $a_{ph}(\lambda)$ is the coefficient of absorption by dissolved organic matter and phytoplankton pigments; $b_{bp}(\lambda)$ is the coefficient of radiation backscattering by the suspension; H is the depth, m; and $f = 1.04/\cos(Q)$ is the index depending on the solar beam refraction angle Q.

The spectral values of absorption coefficients of phytoplankton pigments and backscattering by suspended matter are expressed in terms of the chlorophyll concentration [9] and specific absorbance at the reference wavelength [10]:

$$a_{ph}(\lambda) = A(\lambda)C^{1-B(\lambda)}, \quad (2)$$

$$b_{bp}(\lambda) = b_{bp}(660)\left(\frac{660}{\lambda}\right)^{\xi}, \quad (3)$$

where C is the chlorophyll concentration, mg/m^3; $b_{bp}(660)$ is the specific coefficient of backscattering by suspended matter at a wavelength of about 660 nm; ξ is the particle form and size factor [11]; $A(\lambda)$ and $B(\lambda)$ are the empiric coefficients determined for each channel [9].

During the simulation, a set of vectors of values $R(\lambda) = f\left(C, b_{bp}(660), H\right)$ are calculated, the so-called pairs of input and output data, which are used for the ANN learning.

Further, the sea depth is calculated via the weight coefficients found during the learning by the backpropagation rule. The weight coefficients result from approximation of the physical model of radiation propagation in water and are iteratively corrected toward the configuration that allows the network to distinguish between prototype images of interest. The known data received in the experiment can also be supplied to the network input, thus correcting the network weight coefficients. The diagram of the method suggested is shown in Fig. 3. The vectors of values of

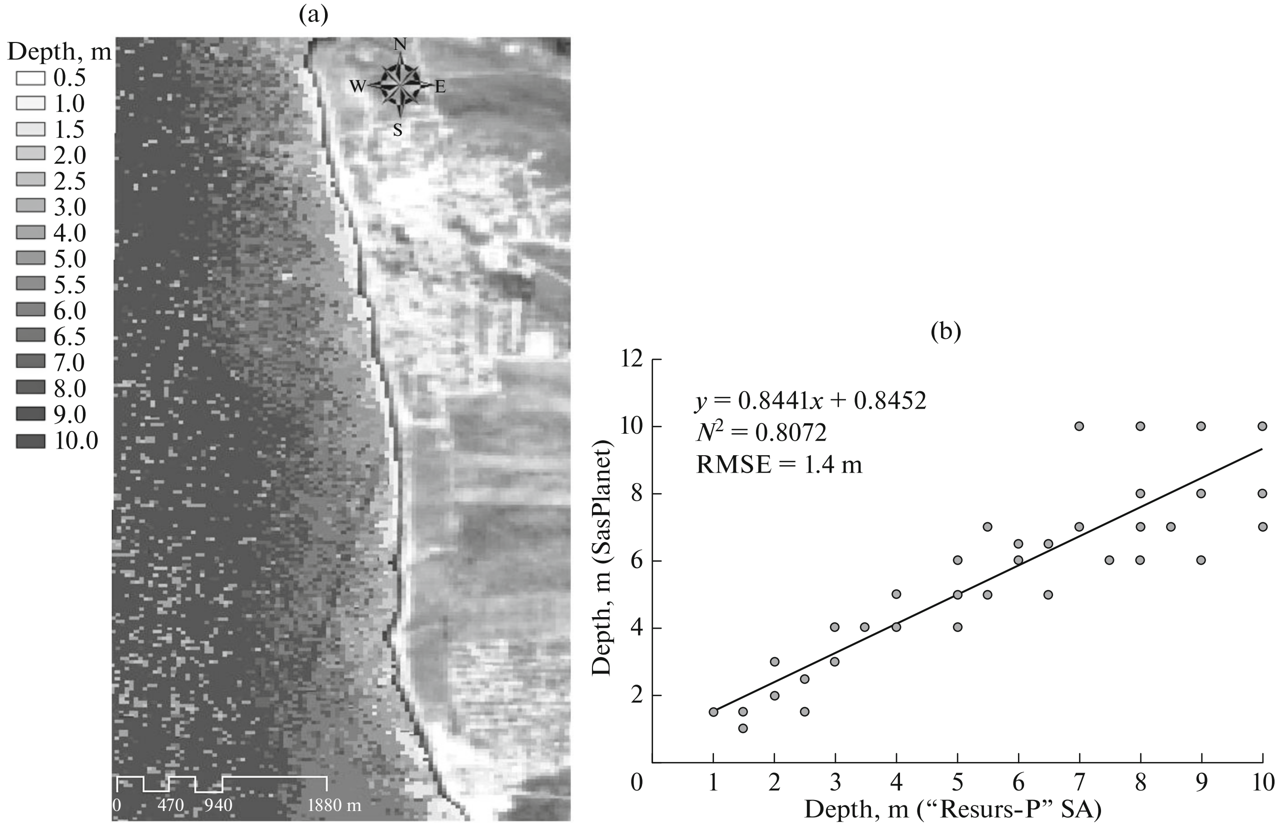

Fig. 4. (a) Depth mapping of a Black Sea region (Kacha) from “Resurs-P” HS images; (b) dependence between calculation results and data on depths from bathymetric maps.

the water surface spectral brightness in three most informative spectral ranges $R(\lambda 1)$, $R(\lambda 2)$, and $R(\lambda 3)$ are taken as input data of the input layer during ANN learning, assuming one spectral band per node. The input data are analyzed in hidden and output layers of the neural network. The analysis results are contained in the output layer, which is a data array that includes the information on the depth H, specific index of backscattering by suspended matter, and the chlorophyll concentration C.

For solution of the inverse problem of depth estimation, it is the most reasonable to use the data on the water depth brightness recorded in three spectral channels, corresponding to violet (400–450 nm) or blue (450–520 nm), green (510–580 nm), and yellow (580–620 nm) spectral regions, or in spectral channels centered at the wavelengths 425 or 485, 545, and 605 nm. This is justified by the fact that the minimal solar radiation attenuation coefficients are observed in transparent waters in the 400–450 nm spectral band and near, and the brightness in the two last spectral channels characterizes the chlorophyll absorption and concentration of suspended matter that determine the backscattering.

At the last stage of the algorithm, results of the depth calculation can be corrected in the case that the known statistical dependences between the spectral brightness and the chlorophyll or suspended matter concentration, expressed through radiation backscattering coefficient by suspended matter, are available.

The concentration C of the total content of chlorophyll a can be determined with the help of known biological optical indices, for example, given in [12]:

$$C = f\left(\mathbf{Z}, \log\frac{R(485)}{R(560)}\right), \tag{4}$$

where $\mathbf{Z}$ is the vector of coefficients of regression between $\log\frac{R(485)}{R(560)}$ and chlorophyll concentration C found from in situ measurements.

The coefficient of backscattering by suspended matter can be found from the regression algorithm based on field measurements with the use of the mean values of the brightness coefficient at a wavelength of about 660 nm [13]:

$$b_{bp}(660) \approx 20a_w(660)R(660). \tag{5}$$

In turn, knowing the specific index of backscattering, it is possible to find the concentration of suspended matter $C_{sm} = Mb_{bp}(660) + N$, where M and N are the linear regression coefficients [14].

Based on the coefficient calculated, the depth is refined and corrected for each pixel of multi- and hyperspectral images, i.e., the network learning is performed with a reduced data set.

RESULTS

The algorithm for depth retrieval was verified by "Resurs-P" HS imagery data, and the reliability of the bottom classification was estimated in the field experiments in coastal areas of the Black Sea. Figure 4 shows the results of depth mapping of the Black Sea area in the vicinity of Kacha (44°46′22″ N, 33°32′19″ E). To estimate the accuracy of the method suggested, bathymetric maps (http://navionics.ru [15]) were used.

In total, about 60 points were used for the verification, by which the linear regression between calculated and mapped depths was constructed, the correlation coefficient and mean square root measurement error (RMSE) were determined. The comparison of HS data processing results and available sea maps have shown their high coincidence: the correlation coefficient is equal to 0.9 in the shallow area of the sea, the differences did not exceed 1.5 m for depths up to 7 m and reach 3 m at depths more than 7 m. In this case, maximal errors correspond to sea areas with high content of radiation-absorbing phytoplankton.

To implement the depth estimation method, the software for thematic processing of multi- and hyperspectral data was developed [16]. The library of spectral characteristics of different bottom types and waters, compiled during flight experiments and ground-based spectrometric measurements, is an inherent part of the software.

CONCLUSIONS

The constant updating of the depths of sea shelf zones is one of key problems of the hydrobiological studies of seas. Solution of this problem is possible with the help of remote data in the visible spectral region; however, the use of them can be limited due to a lack of information on depths at referent points and on light attenuation coefficients during its propagation through the water column. We suggest a method which allows the retrieval of depths in the sea shelf zones even in the absence of this information. The depths are estimated due to complex use of the physical model of radiation transfer in water, multi- and hyperspectral data in the visible and near-IR spectral regions, and an artificial neural network algorithm, which provides a solution of multiparametric problems of nonlinear optimization. An advantage of the ANN is the learning capability and the possibility of finding complex dependences between input and output data while gaining a reliable result, even with incomplete initial information.

The applicability of this approach was shown in the update of Black Sea shelf depths from hyperspectral data of high and low spatial resolution. The bathymetric estimates agree well with open-access depth maps, as well as with field measurement results (with a mean measurement error of 14%). The depth recovery for each pixel was provided by:

– application of water depth brightness coefficient, at least in three spectral channels of the visible spectral region;

– an additional stage of bottom classification, the brightness of which significantly contributes in the coefficient of spectral brightness of shallow waters;

– consideration of interactions between physical factors that form reflecting characteristics of natural radiation by the water surface in a few spectral channels of multi- and hyperspectral data due to the light absorption and scattering by limnic components in the water column;

– ANN learning with the use of dependences between hydro-optical indices (concentration of chlorophyll *a* and suspended matter) and the brightness of upward radiation from the water surface at the wavelengths chosen from field observation results.

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