IDENTIFICATION OF SUBSPECIES OF HIGHER PLANTS BY MULTICHANNEL REGISTRATION OF THE FLUORESCENT RESPONSE

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ABSTRACT
It is shown that by the method of remote registration of fluorescent radiation excited by laser radiation, it is possible to determine not only the species of plants, but also to divide classes of plants belonging to subspecies within the class. To achieve accuracy, discriminant analysis was applied and the quality of the classifier was evaluated.

Full-scale flight experiments performed by us using onboard laser measuring equipment to map the level of fluorescent signals showed distinct differences in their spectral forms depending on the state of ground vegetation, although in a series of these experiments the signal excess over the noise level was not too high. These measurements demonstrated the possibility of confident remote diagnostics of stress conditions of terrestrial vegetation based on the registration of fluorescent responses.

The clarity of such a description consists in the fact that the data characterizing a particular class form a point (or a collection of points) in a multidimensional feature space, with dimension ***n*** - equal to the number of selected channels. Then the task of interpreting remote measurements is reduced to determining whether the ***n*** -dimensional vector of the spectral response belongs to a particular class. The degree of reliability and quality of identification is ultimately determined by how clearly these classes will be separated in the space of spectral features.

KEYWORDS:*remote sensing, laser, fluorescence, spectrum, plant, pattern recognition*

INTRODUCTION

The application of technologies developed on the basis of the use of modern achievements of spectroscopy and laser technology is an important task in environmental monitoring, in particular, in solving problems of optimizing activities in the agricultural sector. The latter provides for monitoring the condition of crops with optical sensors installed on board air or space carriers.

To date, a wide range of methods of laser remote sensing based on fluorescent responses of vegetation have been developed and found application. The advantage of these methods lies in the spatial selectivity of the sensing objects and the absence of optical interference when registering signals at night [1,2].

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Modern remote environmental monitoring methods allow obtaining operational information about the state of vegetation in real time by registering secondary radiation induced by laser irradiation (LIF). At the same time, the most informative for remote diagnostics is the LIF signals in the spectral range of 600 - 750 nm. [4,5].
The spectral forms of higher plants observed in the optical range of 450 - 750 nm are approximately the same due to the identity of the mechanism of photophysical and photochemical reactions occurring in the photosynthetic apparatus (FSA) of plants.

MATERIALS AND METHODS

Nevertheless, in practice, it is possible to detect small visual differences that exist not only between species, but also within the same variety, differing in their physiological state [6,7]. Experiments on prototypes samples have shown that spectral differences are more clearly detected in the fluorescence spectra than in the reflection spectra. It is also encouraging that the characteristic spectrum of fluorescent echo signals during laser excitation from an aircraft differs little from the spectra obtained in laboratory experiments and ground calibration of equipment [8,10].

RESULTS AND DISCUSSION

Full-scale flight experiments performed by us using onboard laser measuring equipment to map the level of fluorescent signals showed distinct differences in their spectral forms depending on the state of ground vegetation, although in a series of these experiments the signal excess over the noise level was not too high.These measurements demonstrated the possibility of confident remote diagnostics of stress conditions of terrestrial vegetation based on the registration of fluorescent responses [9].
Thus, the long-wave peak, which is a shoulder shape in healthy plants (curves *1* in Fig.1), with the development of the disease infected with the fungus *Verticilliumdahlaye* (V.D.), took on an increasingly smoothed appearance with further transformation into a monotonously decreasing curve (curves *2*).

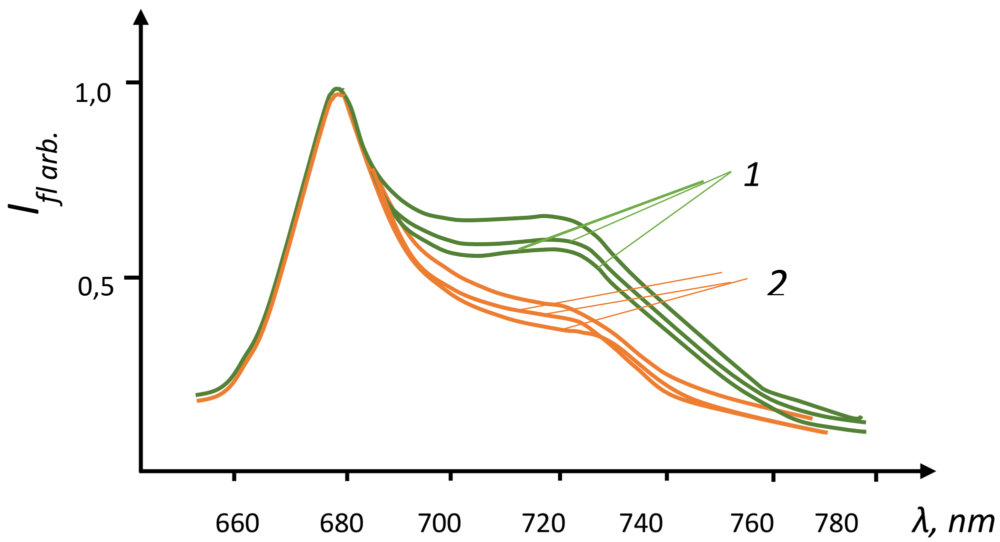

Fig.1. Spectra of cotton leaf bodices depending on its physiological state. *1*- healthy leaves, *2* - plants affected by the fungus*Verticilliumdahlaye (V.d.)*.

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Quite clear differences were found in the structure of the fluorescence spectra corresponding to healthy and diseased plants. At the same time, it should be noted that the pathological condition of plants was spectrally detected even in the absence of visual signs of the disease.

However, there are certain difficulties in classifying plant objects due to the significant overlap of the spectral signature corresponding to groups similar in species. This, in turn, leads to a significant overlap of spectral zones between individual classes (Fig. 2). Therefore, for an adequate classification of objects by their spectral appearance, statistical analysis of data in the range of all possible variations is necessary.

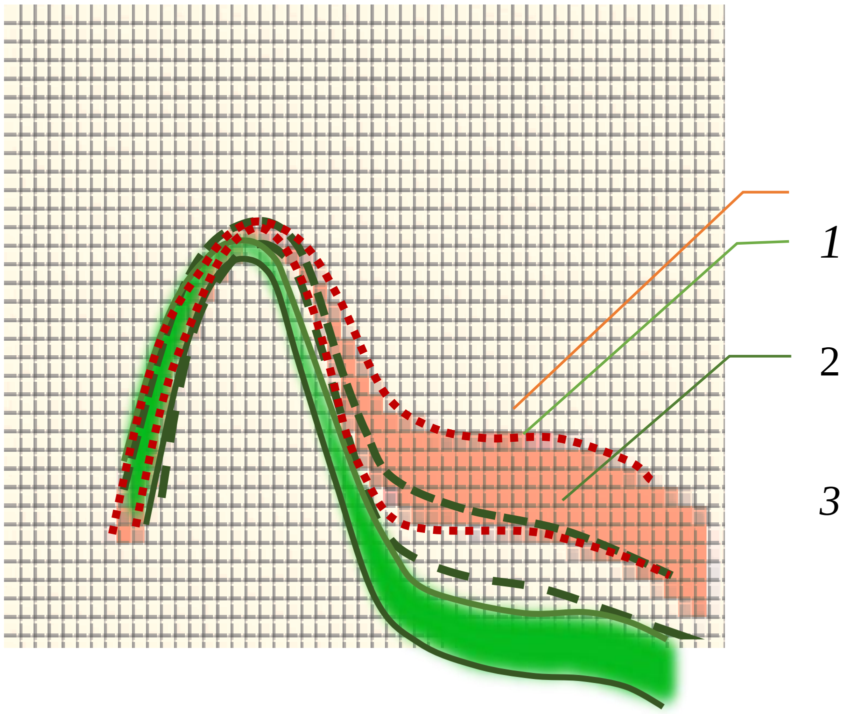

Fig.2. Statistical spread of spectral curves normalized by I_{fl} (680 nm) for various classes of plants: 1 - cotton, 2 - corn, 3 - wheat.

For the most accurate identification of objects based on the analysis of spectral curves, image recognition (IR) methods are used [12]. In this case, the processing of an array of multispectral data is performed over a finite number of discrete quantities formed from the intensities of spectral responses at certain wavelengths.
The clarity of such a description consists in the fact that the data characterizing a particular class form a point (or a collection of points) in a multidimensional feature space, with dimension $\boldsymbol{n}$ - equal to the number of selected channels. Then the task of interpreting remote measurements is reduced to determining whether the $\boldsymbol{n}$ -dimensional vector of the spectral response belongs to a particular class. The degree of reliability and quality of identification is ultimately determined by how clearly these classes will be separated in the space of spectral features.

The separability between classes will be the greater, the more features will be included in the consideration.
Theamplitudevaluesofintensityinadiscretesetofspectralchannelsinthewavelengthrangeof 670 – 740 nmwereselectedassigns.Сравнение кривой статистического ряда, полученного из серии спектров (математическое ожидание $\boldsymbol{\mu}$ и дисперсия $\boldsymbol{\sigma}$ которого были вычислены по

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табулированным данным спектров флуоресценции хлопчатника) с кривым нормального распределения, было установлено, что распределение плотности вероятности интенсивности люминесценции для спектральных данных, используемых далее в качестве обучающих образов, подчиняется нормальному закону (рис.3). Comparison of the curve of the statistical series obtained from a series of spectra (the mathematical expectation μ and variance σ of which were calculated from tabulated data of the fluorescence spectra of cotton) with the curve of the normal distribution, it was found that the distribution of the probability density of luminescence intensity for the spectral data used further as training images obeys the normal law (Fig.3).In addition, the spectral responses measured by two characteristic spectral channels turned out to be dependent. These properties of the signals gave grounds for choosing a discriminant function in the form of a normal distribution [13].

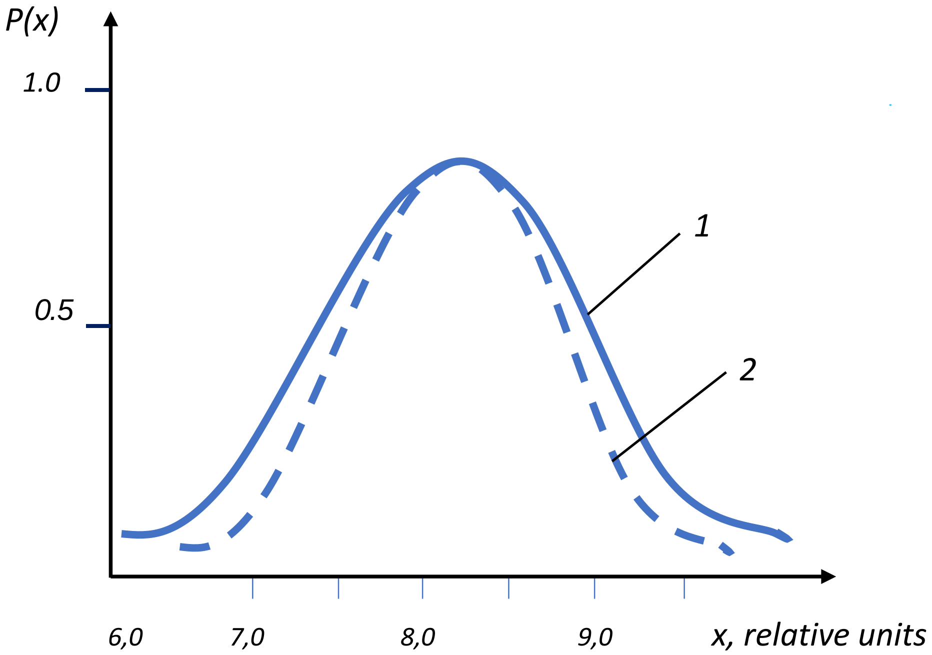

Fig.3. Distribution of the probability density of the luminescence intensity of cotton.
1- is a statistical series of experimental data, *2*- is a curve corresponding to a normal distribution, where ***x*** is the relative magnitude of the signal intensity of the selected spectral channel.

Construction of a multidimensional classifier of spectral data

To solve the classification problem, a method of statistical pattern recognition was chosen based on the calculation of discriminant functions $g_i(X)$ of various classes ***i*** and the evaluation of these functions according to the maximum likelihood rule:

$$g_i(X) = \ell n P(\omega_i) - \frac{1}{2}\ell n|S_i| - \frac{1}{2}(\vec{X} - \vec{\mu}_i)^T S_i^{-1}(\vec{X} - \vec{\mu}_i) \quad (1)$$

where is the a priori probability of class i, i.e. the probability of observing an image from class i, regardless of any other information. For remote measurements, the value of this probability can be obtained from preliminary ground observations.

$|S_i|$-determinant of the covariance matrix,

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$$|S_i| = \begin{vmatrix} \sigma_{i11} & \sigma_{i12} & \ldots\ldots\ldots\ldots & \sigma_{i1k} \\ \sigma_{i21} & \sigma_{i22} & \ldots\ldots\ldots\ldots & \sigma_{i2k} \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_{i\hat{E}1} & \sigma_{i_{K2}} & \ldots\ldots\ldots\ldots & \sigma_{i1KK} \end{vmatrix} \quad (2)$$

составленныйизэлементов - ковариациимеждуканаламиnит (дляклассаi) composed of elements σ_{inm} - covariance between channels ***n*** and ***m*** (for class ***i***)

$$\sigma_{inm} = \frac{1}{q-1}\sum_{e=1}^{qi}(X_l^n - \mu_{in})(X_l^m - \mu_{im}) \quad (3)$$

$l = 1, 2, \ldots\ldots\ldots q_i$; q_i -the number of training images.

- значениепеременнойX (амплитудасигналов) вn, m -спектральномканале, - матрицаобратнаяк ,
X_l^n is the value of the variable X (signal amplitude) in ***n, m***- spectral channel, S_i^{-1} is the matrix inverse to S_i,

$(\vec{X} - \vec{\mu}_i)^T$ - transposedcolumnvector

$$\vec{\text{Ù}}_i = (\vec{X} - \vec{\mu}_i) = \begin{vmatrix} X_{i1} - \mu_{i1} \\ X_{i2} - \mu_{i2} \\ ======= \\ X_{in} - \mu_{in} \end{vmatrix}$$

где - математическоеожиданиепеременнойX i - классавn-спектральномканале. where $\mu_{in} = \frac{1}{q};\sum_{e=1}^{qi} X_l^n$ is the mathematical expectation of the i-class variable X in the n-spectral channel.

The classification algorithm thus boils down to the following: the measured value X belongs to class i $(X \in w_i)$,if the calculated values $g_i(x) \geq g_j(x)$for all$j$=1, 2,…….
Thus, to solve the classification problem, the corresponding discriminant functions of individual classes were constructed according to training images closely related to the set of features inherent in the objects under study. The selection of the most informative, from the point of view of classification of features, in this case, spectral channels, is carried out using a measure of statistical separability of classes i and j in the selected channel λ, as which the normalized distance was used

$$D_{ij}(\lambda) = \frac{|\mu_i - \mu_j|}{\sigma_i + \sigma_j} \quad (4)$$

or the Fisher criterion $F_{ij}(\lambda) = \frac{(\mu_i - \mu_j)^2}{\sigma_i^2 + \sigma_j^2}$ (5)

To find the most informative spectral channels, first of all it is necessary to evaluate the differences between classes in each channel.

Therefore, the normalized distance and the Fisher criterion, in addition to their obvious simplicity, are quite acceptable for such estimates.

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CONCLUSION

Estimates of the informativeness of spectral features in absolute and relative units performed using the normalized distance $D_{ij}(\lambda)$ and the Fisher criterion $F_{ij}(\lambda)$ show that the greatest difference in classes is observed in the region of the first maximum for data in absolute units (Table.1) and in the region of the second maximum for data presented in relative units (Table 2).

Table 1
Mathematical expectation and variance for three different varieties of cotton
(Spectral data in absolute units)
Cotton varieties - "Krasnaya Akala" (cl.1), "6041" (cl.2), "Tashkent-1"(cl.3)

Классы	Каналы (нм)	670	680	690	700	710	720	730	740
I	μ	1,96	3,04	3,27	2,54	2,19	2,15	1,99	1,66
II		1,67	2,47	2,58	1,99	1,84	1,62	1,64	1,37
III		1,39	1,89	1,99	1,54	1,34	1,29	1,17	1,15
I	$\sigma^2 \cdot (E\text{-}02)$	0, 96	1,47	2,10	2,89	2,39	2,39	1,93	1,72
II		1,95	5,13	6,76	1,54	2,47	8,34	1,42	1,08
III		2,06	2,84	3,13	2,00	1,21	1,18	0, 85	0,71

Table 2
Normalized distance D_{ij} (λ) and Fischer's criterion F_{ij}(λ) between 15 day (*class* 1) and 30 day(*class* 2) plants of healthy cotton (spectral data in relative units)

λ (нм)	D_{23}	F_{23}
670	0.051	0.005
680	0.00	0.00
690	0.071	0.008
700	0.083	0.010
710	0.00	0.00
720	0.111	0.019
730	0.173	0.048
740	0.133	0.029

Thus, reliable results are obtained for decoding remote sensing data of vegetation cover using measurements made in the spectrum zones of 670-740 nm, providing the highest spectral resolution. Digital analysis of multichannel data increases the reliability of differentiation of various typological categories of vegetation cover.

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