Identification of Plant Types by RGB Image Received From UAV by Textural Analysis

M.Yu. Kataev¹, M.M. Dadonova¹

kmy@asu.tusur.ru

¹Tomsk University of Control Systems and Radio Electronics (TUSUR), Tomsk, Russia

To date, flying unmanned aerial vehicles (UAVs), with digital cameras on board, have become commonplace. The resulting images are collected in orthophotomaps and more used for visual analysis. A numerical analysis of the content of images is still poorly developed. One of the areas of analysis is the allocation of vegetation in the image and the determination of types. There are many ways to highlight plants in an image, such as texture, color, or index analysis. In this paper, we set the task of processing the image obtained from the UAV, isolating the vegetation in the image, selecting the desired plants from the set, and estimating the area occupied by this plant in the image based on texture analysis.

Keywords: UAV, computer graphics, textural analysis, plant types.

1. Introduction

The implementation of precision farming technology (PFT) makes it necessary to assess the change in the agrotechnical parameters of the land and the parameters of the state of plants during the growing season for each field separately. Information on the spatio-temporal changes in the state parameters of plants will allow us to think through the actions of agricultural workers more accurately, in the right place and in the required volume. Determination of changes in the state of plants is one of the most important elements of PFT. It is clear that the condition of plants depends on weather changes (meteorological parameters), soil properties (agrochemical parameters) and agronomic measures (proper plowing of the soil, fertilizing, etc.). Thus, knowing the state of plants and monitoring this state, it becomes possible to indirectly evaluate the influence of the soil, as well as agronomic measures. During the growth of cultivated plants from the time of planting to ripening, various plants grow on agricultural fields, the type and area of overgrowing of which must be estimated to carry out the relevant measures. Obtaining information about plants in the fields is associated with remote sensing of the Earth (ERS) using spacecraft, airplanes and unmanned aerial vehicles (UAVs). The largest number of works was carried out in the field of passive methods for recording reflected solar radiation by satellite devices (Landsat, Sentinel, MODIS, Vegetation, etc.). The multispectral images of the earth's surface obtained by the satellite cover rather large areas of the territory. However, the practical application of satellite data is associated with the presence of a natural limiter in the form of clouds. The last decade, UAVs have been widely used to study agricultural fields. Measurement data (images in different parts of the spectrum and meteorological parameters) become the basis for the creation of geographic information systems (GIS) of precision farming technology. The processing of such data allows the process of assessing the situation with the state of plants within a single field to be carried out. Naturally, an important step in this process is the identification of vegetation types and mapping for agronomic operations (differential fertilizer application, chemical plant protection products, etc.

2. Main part

A project for identifying plant types from UAV images is being developed at the TUSUR Center for Space Monitoring of the Earth (CSME). The project is developing a complex that includes the Mavic Pro quadrocopter and software. The measurement scheme and the main elements of the software package are shown in Figure 1. From fig. Figure 1 shows that during the flight of the quadrocopter, a set of images of the agricultural field is collected, with some overlap, and an orthophotomap is compiled, which is then cut into separate and equal parts (for example, 50x50 meters or a quarter hectare). Images are stored in the image database and then transferred to the image processing module (includes preliminary and thematic), after which the results are positioned in an open geographic information system. The obtained results of current measurements are recorded in the measurement database in order to subsequently receive the possibility of a spatio-temporal analysis of changes in the state of plants in a particular agricultural field.

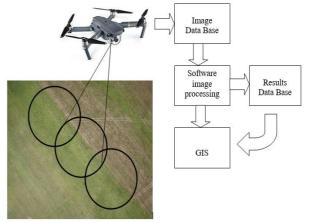


Fig. 1 Measurement scheme and the main elements of the software package

Image processing consists of several stages: preliminary and thematic processing, after which analysis is performed. Analysis solves two problems. The first task is the identification of plants and the second task is to determine the stage of development of the plant (state). At the pre-processing stage, the image is exposed to filters that clean the image from the noise component, changes in the brightness distribution in the image are removed using the "gray world" method, etc. The image is translated in grayscale and reduced to binary. Thus, in addition to color, a set of images is created, which together are further processed. The prepared set of images falls into the thematic processing unit, where the procedure for splitting the image into smaller objects is performed, as shown in Fig. 2.

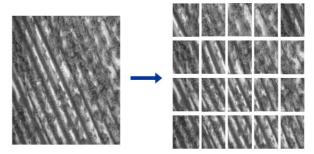


Fig. 2. Splitting the image into small fragments

As well as the pixels of the image itself, increasingly smaller fragments constitute an element of a complex image and have internal numbering. The size of such a fragment varies and is associated with the plant under study (on average, the size varies from 0.5x0.5 to 1x1 meter). The next is the calculation of texture coefficients [1-3] for each fragment. The work selected algorithms based on the statistical approach of texture analysis, the basic formulas of which are given below:

N M d(c i)2.
$P1 = \sum_{i=1}^{N} \sum_{j=1}^{M} \left(\frac{l(i,j)^2}{N+M} \right)$
$(Energy) \qquad \sum_{i=1}^{n} \sum_{j=1}^{n} (N+M)$
(Energy) $l-1j-1$
$\sum_{i=1}^{n} \sum_{j=1}^{n} (i * j * I(i, j) - \mu_{x} \mu_{y})$
$P2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \left(\frac{i * j * I(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \right)$
(Correlation) $\underset{i=1}{\overset{\frown}{\underset{j=1}{\sum}}} (\sigma_x \sigma_y)$
N M
$P3 = \sum_{i=1}^{N} \sum_{j=1}^{N} (i-j)^2 * I(i,j)$
$P^{3} = \sum_{i} \sum_{j} (i - j)^{*} * I(i, j)$
(Contrast) $i=1$ $j=1$
N M
$P4 = \sum_{i=1}^{N} \sum_{j=1}^{N} i - j \star l(i, j)$
$(\text{Dissimilarity}) = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{j=1}$
$P5 = \sum_{i=1}^{N} \sum_{j=1}^{M} \left(\frac{I(i,j)}{1 - ((i-j))^2} \right)$ (Homogeneity)
$P5 = \sum_{i} \sum_{j} \left(\frac{1}{1 - (l_{ij} - i)^{32}} \right)$
(Homogeneity) $ \underset{i=1}{\overset{i=1}{\longrightarrow}} \underbrace{(1 - ((i - j)))^{-}} $
N M
$\mathcal{D}_{\mathcal{L}} = \sum \sum (\mathcal{U}_{\mathcal{L}} \otimes \mathcal{D}_{\mathcal{L}}) - (\mathcal{U}_{\mathcal{L}} \otimes)$
$P6 = \sum_{i=1}^{N} \sum_{j=1}^{N} (I(i, j) * \lg(I(i, j)))$
(Maximum P7 = max(I(i, j)))
(Maximum + r = max(10, j))
$\Sigma \Sigma \Sigma$
$P8 = \sum_{i=1}^{P8} \sum_{i=1}^{P2} l^2(i,j)$
$(Energy) \qquad i=1 j=1$
N M
$P9 = \sum_{i=1}^{N} \sum_{i=1}^{M} \left(\frac{I(i,j)}{1+ i-j } \right)$
(11 + i - j)
(Homogeneity) $\overline{i=1} \overline{j=1}$

For each formula, the values of N, M are set based on the number of pixels in the fragment and depend on its physical size (in meters). For each fragment, a table is compiled with the values of the coefficients (an example of the table is shown in Fig. 3).

1 fragment	2 fragment	3 fragment
7,594E-3	7,302E-3	7.111E-3
7,916E+3	7,849E+3	8,058E+3
1,238E+3	1,205E+3	1,385E+3
9,342E+1	8,725E+1	9,484E+1
1,272E+0	1,233E+0	1,204E+0
5,953E+0	5,768E+0	6,008E+0
2,597E-3	2,315E-3	2,457E-3
8,974E-3	9,124E-3	8,702E-3
6,575E-2	6,232E-2	6,651E-2

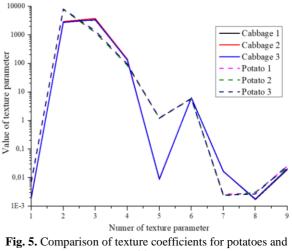
Fig. 3. The result of the calculation of texture features (potatoes)

The template is built on the basis of a set of images of a known plant and the values of the texture analysis coefficients are determined for it. As can be seen from the presented calculation of texture coefficients in Fig. 3, they have a slight scatter, which is due to the fact that in each fragment, except for the plant itself, the earth enters, but its area is much smaller than the plant itself. For example, we can give another plant (cabbage, see Fig. 4), for which the texture coefficients differ from the calculated coefficients for potatoes.

1 fragment	2 fragment	3 fragment
1,990E-3	1,930E-3	2,041E-3
2,890E+3	2,938E+3	2,743E+3
3,334E+3	3,764E+3	3,404E+3
1,354E+2	1,426E+2	1,323E+2
8,747E-3	8,813E-3	9,089E-3
6,393E+0	6,326E+0	6,243E+0
1,672E-2	1,689E-2	1,649E-2
1,722E-3	1,788E-3	1,817E-3
1,926E-2	2,040E-2	2.087E-2

Fig. 4. The result of the calculation of texture features (cabbage)

From a comparison of the values of the texture analysis coefficients shown in Fig. 5. Figures 3 and 4 show that some of them have close values, however, in the aggregate, significant differences are observed (see Fig. 5).



cabbage

The results obtained allow us to develop a template based on uniquely identified fragments for a given plant, which must be compared with other fragments of the image. Comparison of the texture analysis coefficients for each image fragment allows you to select those fragments that are closest to the template by comparing the texture analysis coefficients. The accuracy of this approach for images of potatoes and cabbage gives 78%, which is a fairly large value. We propose to use these data to solve the problem of classifying the image of an object about its belonging to one of the given plant types.

3. Conclusion

The proposed approach is implemented in the form of a program that is able to solve practical problems arising in agriculture. The result of the system's work is the answers to the questions: what plant is in the image, the ratio of the number of biomass to the total field area. Processing of real images for the field of potatoes and cabbage showed a high efficiency of isolating plants of a given type on the field by texture coefficients. The development of the approach and increasing the accuracy of the approach is seen by the authors in the application of more complex algorithms for texture analysis and color histograms. As an alternative to this method, the application of machine learning methods (for example, convolutional network and deep learning) is used.

4. References

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