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DEVELOPMENT OF THE HARDWARE AND SOFTWARE COMPLEX FOR FERTILIZER APPLICATION ON AGRICULTURAL FIELDS

Summary

In the article developing of hardware and software complex for fertilizer application on agricultural fields is described. The complex is intended for environmental pressures reduction in case of treatment and prevention of agricultural vegetation diseases. The developed technique of data obtaining by UAV, processing of remote sensing data and preparing of control data for system of fertilizer application is considered.
Key words: *precision agriculture, disease detection, object classification*

1. Introduction

Every year a need for information obtained using remote sensing data (RSD) is growing. RSD are used in problems of cartography and land cadastre [1], an agronomy and a precision agriculture [2-7], a forestry [8-11], a development of water systems [12], an environmental monitoring [13] etc. Constantly growing requirements for perfect data processing systems are increasing, because information is a key element in decision-making, and amount of information of different degrees of complexity increases. One of major problems arising in connection with creation of modern information systems is automation of processing of raw data presented as images.

One of the most important areas of image processing is a precision agriculture area. Efficient processing of raw data allows reducing material and other costs in problems associated with crop cultivation and forecasting, a monitoring of level of crops germination and many other applications. The solution of such problems involves using of geographic information systems (GIS), which combine necessary techniques for image processing. There are a number of systems for precision agriculture tasks: The Monitoring of Agriculture with Remote Sensing (MARS), Variogram Estimation and Spatial Prediction plus ERror (VESPER), Ag Leader Insight etc. These systems are based on remote sensing processing methods, which allow effective detecting field areas that are infected by plant diseases. Detection and recognition of an infection on early stages of its development reduces costs of plant protective measures. There are two main approaches for detection of the infected areas: spectrometric and optical or visual [14-18]. A number of institutes and companies around the world deal with researches in this area, which include Research and Development Center "ScanEx", company ESRI, company ERDAS, Inc. There are also a number of research centers that solve the problem of precision farming: Australian Centre for Precision Agriculture, Centre for Precision Farming, Ohio State University Precision Agriculture and others.

2. Functions and structure of the complex

The main task of developed hardware and software complex is preparing of morbidity maps of agricultural vegetation (potato) for fertilizer application for healing and prevention of plant diseases.
A series of algorithms for additional feature extraction and processing for agricultural fields images of different spatial resolution are developed by the author [19]. These algorithms can be used to creation a technique of data processing which is used as basis for developing of decision making support system (DMSS) for the complex for precision farming tasks. The DMSS is used as core of the developed complex.

The technique of monitoring the vegetation in the applications of precision agriculture is used for solving the following tasks:
– Mapping of irregularities of agricultural vegetation state, taking into account states of vegetation (presence/absence of disease), and the number of green plants in some areas of the field. For this purpose, identification and segmentation algorithms that take into account brightness, texture and fractal features of aerial images of agricultural vegetation.
– Mapping of vegetation diseases on the basis of their brightness features. It uses pattern recognition algorithms proposed by the author, which allow recognizing diseased plants and identifying disease.
– Preparation of maps of which can be used as input data for plant protection systems. This can be done using the algorithm forming maps of morbidity rate that indicate parts of the agricultural field for fertilizers application.

Thus, to make decisions about state of the vegetation and amount of applied fertilizers, following steps should be performed:
1. Performing of pre-processing: filtering, white balance correction, data georeferencing.
2. Calculation of the additional features for each processed image: texture, fractal (fractal dimension) and color (ranges saturation and hue of different classes of objects, the normalized reduced histogram for training set of neural network classifier).
3. Performing of multi-criteria threshold and joint segmentation of color, texture and fractal features to detection of different areas of the original image: vegetation (affected and healthy), soil, vegetation and soil boundary, foreign objects.
4. Training of the proposed neural network classifier and recognition of aerial photographs to forming morbidity map

which shows areas of soil, healthy and diseased plants and used as a basis for calculation of statistical indicators of productivity.
5. Forming of maps of morbidity rate which is input of control subsystem of device, which carry out application of plant protection products for their treatment.

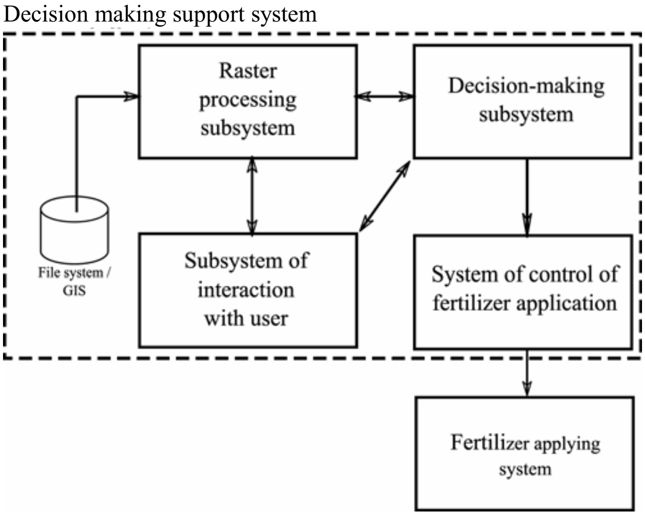


Fig. 1. The scheme of hardware and software complex for precision farming tasks

The proposed hardware and software complex is designed for monitoring of beginning and development of diseases of vegetation as a part of GIS for precision farming. Such complex must perform the following tasks:
– loading of original data and storing of formed maps of morbidity,
– providing of user interactions, including control of decisions which are received by system:
– detection of irregularities of vegetation using aerial photographs of agricultural fields:
– recognition of the state of vegetation and mapping of disease:
– forming of input data for control systems of fertilizer application device of agricultural vegetation.

Structure of the complex is shown in Figure 1. Main components of the complex are:
– File system/GIS. It is designed for storage of original data.
– Raster processing subsystem. It is designed to perform processing raster aerial photographs of agricultural fields: segmentation, recognition, mapping.
– Subsystem of interaction with user. The subsystem allows user to monitor and control automated processing of aerial photographs.
– Decision-making subsystem. It is designed for deciding on need for fertilizers and their quantities on the basis of results of data of system of control of fertilizer application and user-defined parameters (choice of processing algorithm and its parameters).
– System of control of fertilizer application. It is designed for task forming to system of fertilizer application. It contains data, which depending on the density of plant diseases, allow to prepare a solution of desired concentrations of fertilizer.

3. Original Data

Agricultural field color images received with help of high resolution digital shooting are an object of our research (fig. 2). Lower value of this quantity equals higher spatial resolution of image. In this article, if side of square is less than 0.6 cm, a spatial resolution is considered as high, otherwise – as low. We need to solve the problem of recognition for mapping of a disease. This can be done by recognizing the original image or by recognizing the received special area.

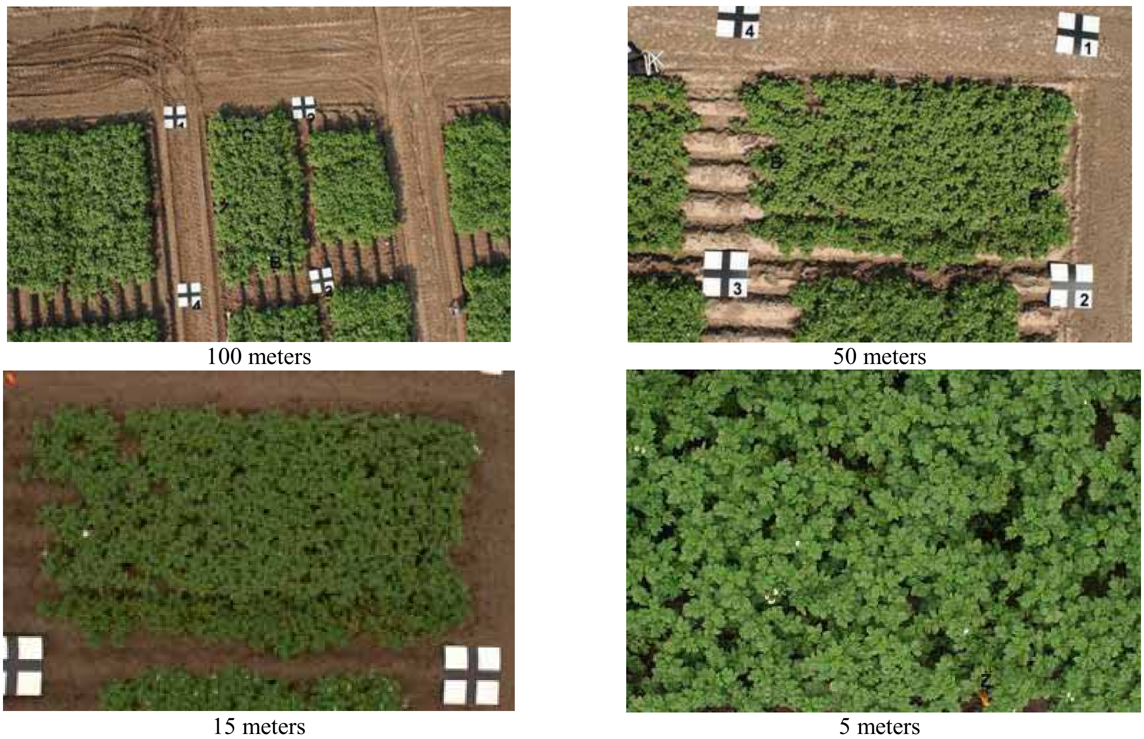


Fig. 2. Examples of original aerial photographs

4. Textures and Fractals

A texture is one of the major characteristics used for identification of objects or areas on the image. It represents two-level structure [20]:

– at the top level – a set of base elements connected by some spatial organization:

– on bottom – base elements representing casual aspect.

The structures are subdivided on fine-grained, coarse-grained, smooth, granulated and undulating in according with used base attributes and interactions between them. In view of interaction degree of the base elements the structures are subdivided on strong (interaction submits to some rule) and weak (interaction has casual character).

An essence of the proposed method of textural characteristics calculation consists in calculation of separate channel images signatures with their subsequent association with use of factors which values depend on vegetation type and condition. An example of the obtained textures is shown in fig. 3. The example of textural characteristics calculation result is resulted on fig. 3, where visualization of calculated values Contrast is resulted. Contrast approximates 1 at a small variation of original data, and it vanishes at greater variation [21].

Fractal signatures calculation is based on the fact that quantified values of bidimentional signal intensity are located between two functions named the top and bottom surfaces [22]. Top surface U contains a set of points which values always exceed an intensity of the original signal. Bottom surface L has values of points which always are lower of the original image.

Results of fractal signatures calculation algorithm are presented in fig. 4 (visualization of the calculated values fractal signatures is resulted). The quantity $1 < D < 2$ more, than cut more up and non-uniform is image area.

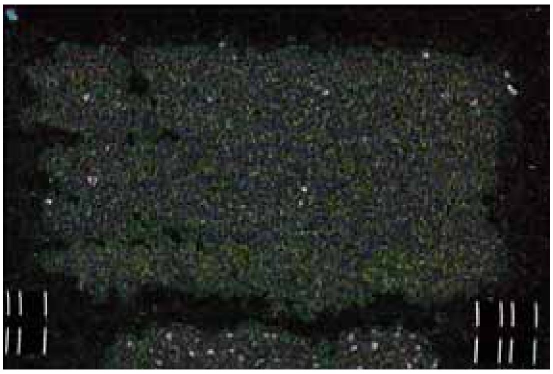


Fig. 3. Textural characteristics for the photograph shown in fig. 2 (15 meters).

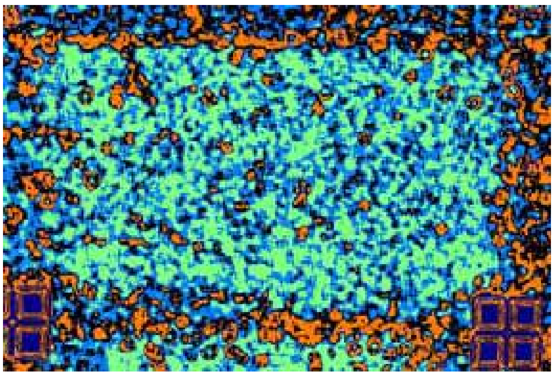


Fig. 4. Fractal signatures of various image areas

5. Joint Fuzzy Segmentation

The essence of the segmentation algorithm is the co-processing of the source images and their fractal and textural features (i.e., an original color image is complemented by images of texture and fractal features).

Calculated fractal signature and textural features of the images is carried out for individual channels and subsequent association performed using coefficients whose values depend on type and condition of vegetation.

Matrixes of color features of original image, as well as the textural and fractal features computed for each color channel of the original image are used as the feature space over which a decision is made.

Color ranges of corresponding healthy and diseased parts of potato fields obtained from an expert are used as color features. The algorithm is intended for segmentation of two-dimensional data representing matrices of various features of the original image such as color channels, textural and fractal features. Thus, the segmentation algorithm is executed in an N-dimensional space of attributes (where N is the number of characteristics used) where each dimension can be taken with a certain weight coefficient.

Thus, the algorithm consists of the following steps:

Step 1. Processing of the original images for the extraction of additional information of channels representing matrices of textural and fractal characteristics of each original image color channel separately.

Step 2. Joint segmentation of the textural and fractal characteristics matrices and the original color channel images (using the Fuzzy C-means (FCM), Gustafson-Kessel (GKC) or Gath-Geva (GGC) clustering algorithm. The number of segments is chosen on the basis of validity criteria described in [23]).

Step 3. Special area map building on the basis of the results of the joint segmentation.

Obtained segmentation result (fig. 5) allows in an automatic mode to detect areas on which there is a disease development. The knowledge of an allocation of such areas allows determining requirement of those or other agricultural fields areas for fertilizers and other chemicals. It allows making agricultural works more effective and less expensive.

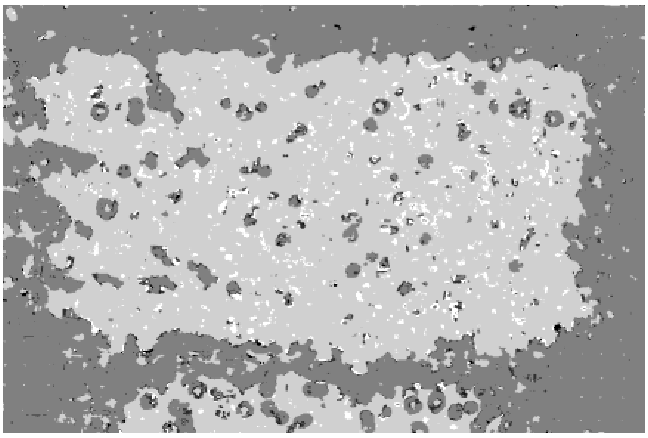


Fig. 5. Joint segmentation result example

6. Color Features

6.1. RGB

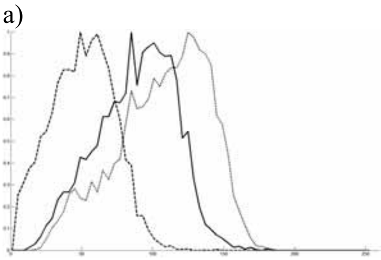
Next step of processing is image recognition based on analysis of color features of various objects types. The analysis showed that within the same type, the features differ slightly and are independent of spatial resolution. At the same time these features have some differences for different objects types. These differences in color features for each color channel (R, G, B or H, S, V) separately are offered to use for processing.

Color features of images are represented as normalized reduced histograms. A number of individual brightness elements is decreased and can be equal to zero for a small images that creates distortions of a histogram. To reduce influence of the distortions it is proposed to use a histogram of intervals of brightness – the histogram based on a set of elements of brightness in each segment. Such histogram is called a reduced. To ensure interoperability between the histograms of various sizes of images we use a normalization procedure (fig. 6).

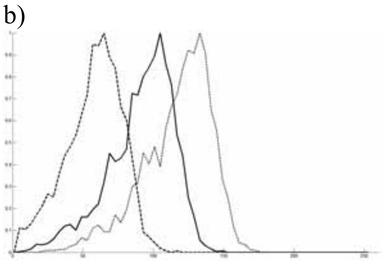
$$res(i) = \sum_{k=(i-1)*4+1}^{i*4} hist(k), i = 1,...,64, \quad (1)$$

where *res* – histogram array with reduced number of elements.

a)



b)



c)

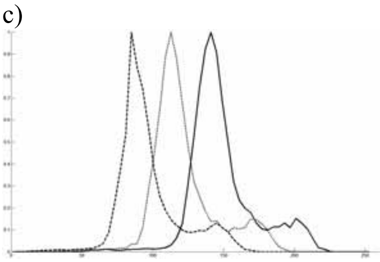


Fig. 6. Normalized reduced histogram constructed for the RGB-representation: a) “diseased plants”; b) ”healthy plants”; c) ”soil”

Normalized histogram for one color channel of image of a given type object (size $M \times N$ pixels) is formed by the following algorithm:

1. Calculated histogram (*hist*) for the selected image areas. The histogram is an array of numbers dimension 256, each of which – the number of elements of a halftone image corresponding brightness.
2. Reduced histogram (*hist*) with 256 points to 64 values – amount calculated for each segment containing four values of original histogram:
3. Calculated maximum value of the histogram (*res*):

$mx = \max(res(i))$, for $i = 1, \ldots, 64$, (2)

4. Performing the normalization of the values of the histogram to the range [0, 1] by dividing the values in array histogram *res* on *mx*:

$res(i) = res(i)/mx$, for $i = 1, \ldots, 64$, (3)

This algorithm is used for each color channel section of original image. As a result three normalized histograms with a reduced number of readings, which together make up an array of 192 values, which is used for classification.

6.2. HSV

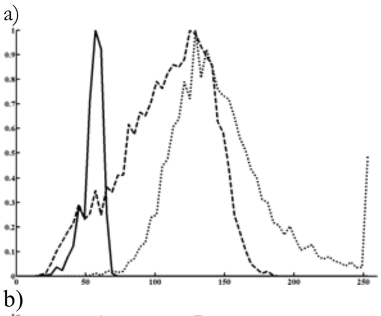
In addition to using color space RGB, you can use color space HSV (Hue, Saturation, Value). To go from RGB to HSV should perform the following transformations:

1. Convert RGB channels with a range [0, 255] to range [0, 1], for which color value at each point of original image is divided by 255.
2. Image color values are calculated in space of HSV for each point of original, where H takes values in range [0, 360), and S, V – in range [0, 1].
3. Transform values obtained for H, S and V to the range [0, 255]:

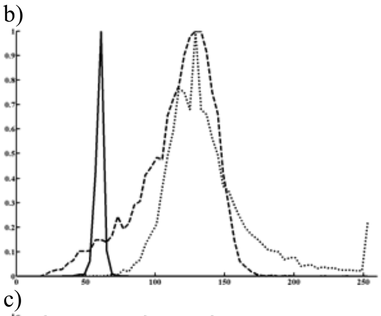
$H = H / 360 \times 255$: (4)
$S = S \times 255$:
$V = V \times 255$.

Further work with the data obtained repeats work with original RGB-data – construct normalized reduced histograms. Figure 7 shows the normalized histograms for reduced color space to HSV (a solid line shows the value of channel Hue, dashed – Saturation, dashed – Value).

a)



b)



c)

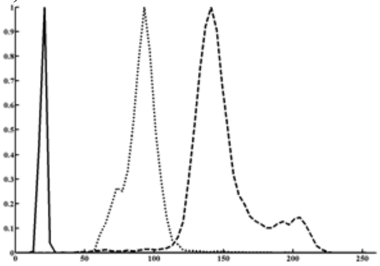


Fig. 7. Normalized reduced histogram constructed for the HSV-representation: a) “diseased plants”; b) ”healthy plants”; c) ”soil”

7. Perceptron as a Classifier

To classify image areas are encouraged to use a multilayer perceptron [24], with $N \times L$ inputs (where N – number of segments of the histogram, which is input to a normalized histogram with a reduced number of readings along the axis X, L – number of channels), with one hidden layer, containing 32×3 neuron (number of neurons in the hidden layer is chosen experimentally), and an output layer containing three neurons corresponding to object types, images. In all neurons of the perceptron, logistic activation function has sigmoid shape.

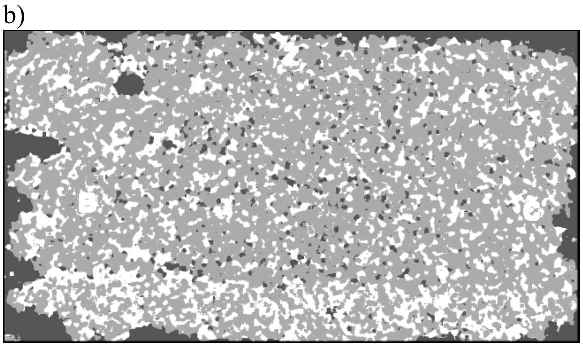
Data sample for classification by scanning the original image through a "sliding window" size $K \times K$ pixels.

To adjust weights of the perceptron algorithm back-propagation is used. In this case, normalized histograms obtained from images of objects selected by operator used as training sets for perceptron.

Training of perceptron performed on low resolution images of same type objects, relevant areas of field related to one of these classes of objects selected by expert of 100 images for each class. In this particular coverage and spatial resolution were not considered in the training set contains images with different lighting conditions and with different spatial resolution. Samples of potato fields aerial photographs recognition are shown in figure 8.

a)

b)



c)

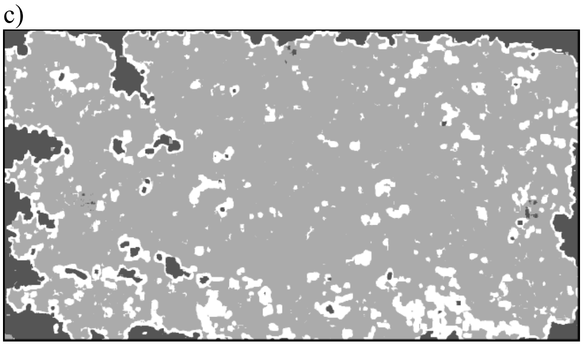


Fig. 8. Samples of potato fields aerial photographs recognition: a) original image; b) recognized using RGB; c) recognition using HSV

8. Technique of monitoring

We propose the following technique of monitoring in the developed hardware and software complex:

1. Forming set of features and selection of values of their parameters.

2. Building maps of specific areas of agricultural fields (for example, parts of the field with diseased plants) with using of the joint segmentation algorithm.

3. Training of neural network classifier of the DMSS with using expert data on healthy and diseased areas agricultural vegetation.

4. Performing of image recognition parts of the field, which was classified as affected by disease.

5. Performing georeferencing of the maps and storing them in the GIS database.

6. Making decision on need for fertilizers and their quantities on the basis of the maps.

7. Calculation of quantity of fertilizers to be applied, and to transmit corresponding command to fertilizers application on the basis of maps and data obtained in real time (for example, camcorder mounted on watering system).

As real time can be used:

– Data from GPS or GLONASS. In this case, the control system using navigation information calculates the required quantity of fertilizer, based on data of specific areas map.

– Data from color cameras. In this case, the control system can adjust in real time the data of specific areas map, for accepting more accurate decision, that increase efficiency of tasks solving.

The complex in automated mode detects areas affected by disease. Information about of the location of such sites is used to determine the needs of various sections of agricultural fields in fertilizers and other chemicals. This increases efficiency and reduces the cost of farming. Morbidity rate maps are input data for the system of fertilizers applying. In this case, the quantity of applied fertilizers directly proportional to rate of morbidity, indicated on the map.

9. Conclusion

The technique of recognition of vegetation state for decision support system for monitoring agricultural fields was proposed. The proposed algorithms for image segmentation, identification of specified areas and neural network classification are used as core of the decision support system. These algorithms allow to build additional features and to configure algorithms for processing specific images in order to reduce time complexity and improve reliability of identification.

The structure of the complex, which was based on the proposed technique of recognizing the state of vegetation from aerial photographs stored in GIS is proposed. The results of data processing can be used in the control system of fertilizers applying mechanisms for treatment and prevention of diseases of potato.

Scientific significance of these results consists in creation of new algorithms of detection diseases areas of agricultural plants fields which allow highlighting detail of diseased areas, which can be used in problems of precision farming.

Practical importance relies on application of the developed complex for cultivation of green products at reduced cost.

Possible area of application is in remote sensing of the Earth (in precision farming, forestry).

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