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Based on Perceptron Object Classification Algorithms for Processing of Agricultural Field Images

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Abstract: *Neural network algorithms of object classification are considered in the paper applying to disease area recognition of agricultural field images. The images are presented as reduced normalized histograms. The classification is carried out for RGB-and HSV-space by using of a multilayer perceptron.*

Keywords: precision agriculture, perceptron, disease detection, object classification, training sample.

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.

Remote sensing methods 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]. The spectrometric approach allows detecting a number of infections on very early development stages. For example, a change of reflective features of potato plants in infrared area allows identifying phytophthora even before appearance of visual features [14, 17]. In spite of that fact a development of optical methods for infection detection takes place both for independent systems and for spectrometric ones what increases a quality of disease recognition of affected areas of agricultural fields. They should include the following ones:

- methods and algorithms for preprocessing and selection of features of the objects in agricultural fields images based on combining a spectral approach and a separation in space color coordinates;
- artificial neural network (ANN) models for fuzzy data clustering and classification methods.

The basic concept of precision agriculture is the fact that a vegetation cover is not uniform within a single field. Up-to-date technologies are used to evaluate and detect these irregularities: global positioning systems (GPS, GLONASS), special sensors, aerial photographs and a satellite imagery, as well as special software system based on GIS. RSD are used for more accurately evaluation of a seeding density, calculation of application rates and crop protection, more accurate prediction of yield and a financial planning. Also, it must take into account local peculiarities of soil and climatic conditions. In some cases it may allow easier to adjudicate the reasons for deterioration of vegetation [7].

Sometimes precision agriculture is associated with desire to maximize profits applying fertilizers only on those portions of fields where fertilizers are needed. Following this, agricultural producers use technologies of variable or differential fertilization in those areas of the field, which are identified with help of GPS-receivers and where requirement for a certain rate of fertilizers is identified using yield maps. Therefore, a rate of application or spraying is less than an average in some areas of field, and a redistribution of fertilizers takes place in favor of areas where the rate should be higher, and thus, an application of the fertilizers are optimized.

Agricultural field color images received with help of high resolution digital shooting are an object of our research (fig. 1). Rectangles show the same area of field received from 5 m height. In this case, a spatial resolution of image refers to size of square of original object, contained in one pixel. 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 initial image or by recognizing the received special area.

Object recognition is one of the main stages in the image analysis. Object recognition task is stated in the following way. It is necessary to discover a map of an input pattern X to Y, where Y is a class of the input pattern. The map is defined by set of pairs (input pattern, class of pattern). The number of pairs (training samples) is significantly less than the possible amount of pairs (input, output). So training set consists of training samples.

If images are strongly distorted, it is very difficult to find informative features of the object. In common case we have distortions of two types: brightness characteristic or position of a pixel is changed.

Neural network (NN) classifiers give the most robust classification in the case when images are strongly distorted. There is a number of NN suited to this goal: a multilayered perceptron, a network of radial basic function, an ART network (Adaptive Resonant Theory), Hopfield network, Kohonen self-oganasing map.

Two algorthms of object classification based on a perceptron and an histogram analysis of RGB- and HSV-color features are procosed in the paper.

2. IMAGE RECOGNITION

2.1. RGB

Analysis of color features of various objects types in images showed that they differ slightly within the same type, and they are independent both of a height from which the images are taken, and of time of shooting. These color differences for each color channel (*R*, *G*, *B*) are offered to use for monitoring of agricultural fields diseases.

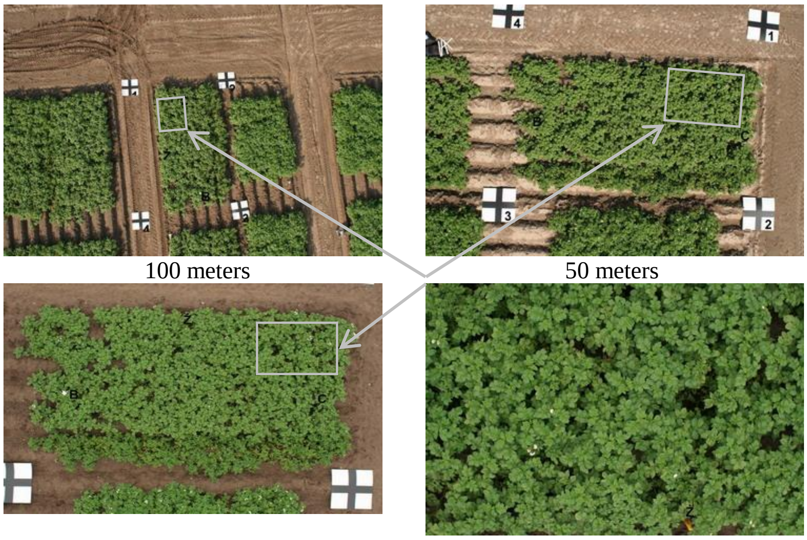


Fig. 1 – Examples of initial aerial photographs.

Figure 3 illustrates an influence of quantity of the ranges on the reduced and normalized histograms for the images of different classes of objects shown in Figure 2, where solid, dashed and dotted lines indicate the histograms of red, green and blue channels respectively. Histogram distortions are seen in Figures 3d-3f – a smoothness decrease and an appearance of a large number of gaps, i.e. regions with zero values in the histogram. A loss of data also can be seen by comparing Figures 3b and 3c or Figures 3e and 3f (a detail is missing if the number of segments is reduced from 64 to 16. In this case a difference of color features of objects of various types may be insufficient for classification (Figure 3c, 3f, 3i). To minimize a data loss specified by variability the number of the ranges should be chosen so that the reduced histogram gets smoother than the original one, but contains enough data about the variability. The partition to 64 segments on *X* axis was selected during the experiments.

A normalized histogram for one color channel of an image of size *M*x*N* pixels is formed by the following algorithm:

Step 1. Calculating histogram (*hist*) for the selected image areas. The histogram is an array of numbers of range [0,255], each number represents an amount of elements of specified brightness on a halftone image.

Step 2. Calculating reduced histogram (*hist*) with 256 points to 64 values – amount calculated for each segment containing four values of original histogram:

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

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

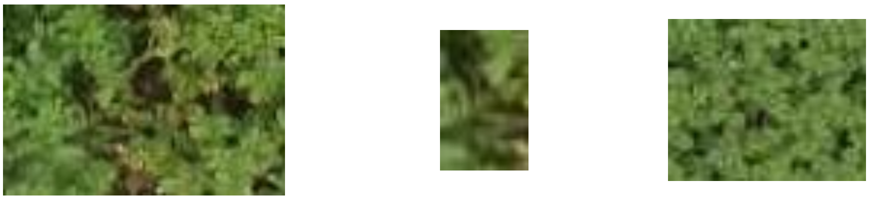
Step 3. Calculating the maximum value of histogram (*res*):

$$mx = \max(res(i)), \text{ for } i = 1, \ldots, 64,$$

Step 4. Normalization of histogram (*res*) to the range [0, 1] by dividing values res of the histogram array on *mx*:

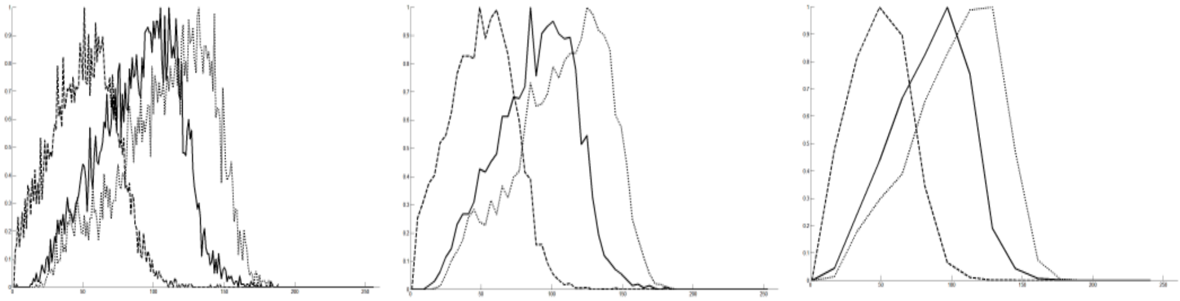
$$res(i) = res(i) / mx, \text{ for } i = 1, \ldots, 64,$$

This algorithm is used for each color channel of the original image. As a result, three normalized reduced histograms are obtained, that together make up an array of 192 values, which is used for classification.

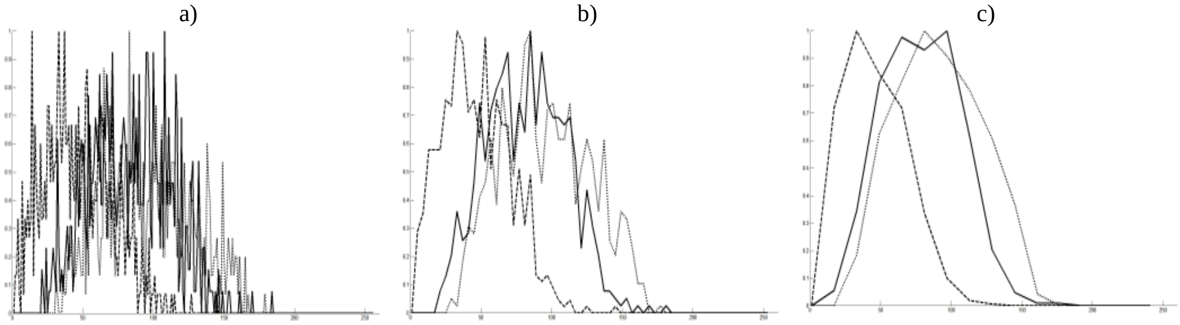


a) b) c)

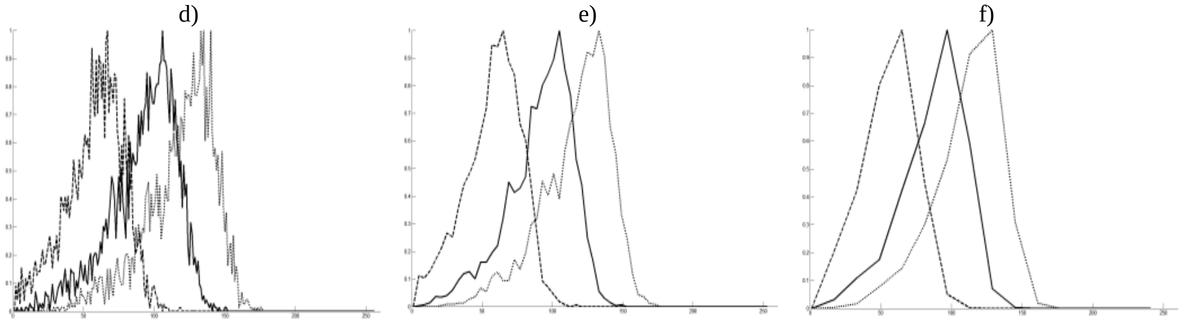
Fig. 2 – Image of diseased plants areas with size 97x66 pixels (8.8a) and 20x32 pixels (8.8b), area of healthy plants with size of 62x50 pixels (8.8c).



a) b) c)



d) e) f)



g) h) i)

Fig. 3 – Histograms: the original (a, d, g), reduced to 64 segments (b, e, h), up to 16 segments (c, f, i) for objects 2a, 2b, 2c respectively.

2.2. HSV

Color space HSV (Hue, Saturation, Value) can be used in addition to color space RGB. To go from RGB to HSV should the following transformations are performed to obtain HSV representation of given RGB image.

1. Converting RGB channels with range [0, 255] to range [0, 1] by dividing color values of pixels of the image by 255.

2. Calculating HSV color values by the following formulas:

$$H = \begin{cases} 0, \text{ если } \max(R,G,B) = \min(R,G,B); \\ 60 \times \dfrac{G-B}{\max(R,G,B)-\min(R,G,B)} + 0, \text{ если } \max(R,G,B) = R, G \geq B; \\ 60 \times \dfrac{G-B}{\max(R,G,B)-\min(R,G,B)} + 360, \text{ если } \max(R,G,B) = R, G < B; \\ 60 \times \dfrac{B-R}{\max(R,G,B)-\min(R,G,B)} + 120, \text{ если } \max(R,G,B) = G; \\ 60 \times \dfrac{R-G}{\max(R,G,B)-\min(R,G,B)} + 240, \text{ если } \max(R,G,B) = B; \end{cases}$$

$$S = \begin{cases} 0, \text{ если } \max(R,G,B) = 0; \\ \text{иначе } 1 - \dfrac{\min(R,G,B)}{\max(R,G,B)}; \end{cases}$$

$V = \max(R, G, B)$.

where H possesses the values in range [0, 360), and S, V, R, G, B – in range [0, 1].

3. Transforming values H, S and V to range [0, 255]:

$H = H / 360 \times 255$;

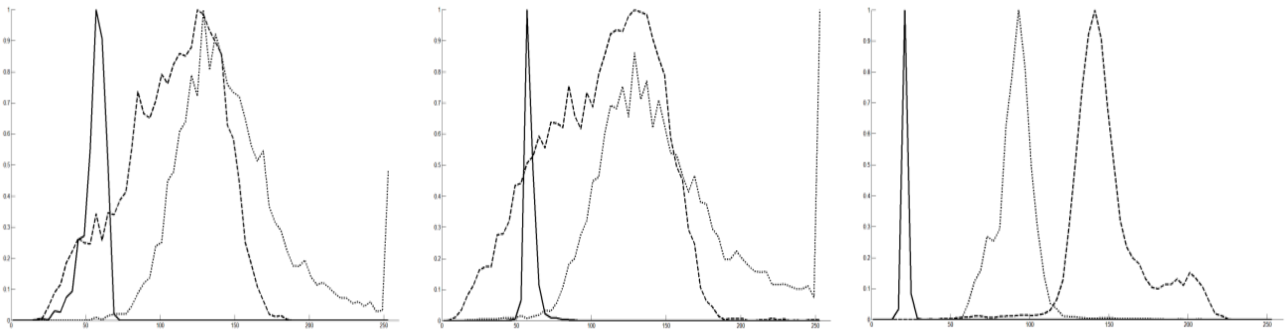
$S = S \times 255$;

$V = V \times 255$.

Further, the proposed image processing algorithms are applied to HSV data. RGB-data – construct normalized reduced histograms. Figure 4 shows the normalized histograms for reduced HSV color space, where solid, dashed and dotted lines shows the values of channels Hue, Saturation and Value respectively.

2.3. PERCEPTRON AS CLASSIFIER

The task of object classification on images is partially solved by using texture feature Contrast of quantity measure s measure of local variations on the images. Depending on degree of image variability textural feature Contrast takes higher values for images having high divergent objects and lower values – in case of low divergent objects. Analysis of texture feature Contrast showed that the soil plots are low divergent and areas of vegetation – high divergent [19]. Thus, Contrast can be used to separate image plots of soil. This will reduce the amount of computation that may be important in processing large amounts of data. In contrast to soil, leaves of vegetation are equally low divergent on images of high spatial resolution. A high variability is preserved only at edges of leaves, which does not correctly separate classes of "soil" and "vegetation". To use the texture feature Contrast for mapping image areas containing soil, some transformations should be performed. It is proposed not to use arrays of features of channel images but halftone images, those visualize the arrays. This allows expert to monitor and adjust process as well as widespread use of image processing algorithms for conversion.



a) **b)** c)

Fig. 4 – Normalized reduced histogram constructed for the HSV-representation: a) "diseased plants"; b) "healthy plants"; c) "soil".

To classify image areas a multilayer perceptron [20] is proposed to use with $N\times L$ inputs (where N – a number of segments of the reduced histogram, L – a number of channels), one hidden layer, containing 32×3 neurons (the number of the neurons is chosen experimentally), and an output layer containing three neurons corresponding to object types of the images. All neurons have a logistic activation function in a sigmoid form.

The back-propagation algorithm is used to adjust weights of the perceptron. In this case, the input of the perceptron fed normalized histograms obtained from images of objects selected by an operator. A data sample for learning algorithm is formed by scanning the original image through a "running-window" size KxK.

Training of perceptron performed on low resolution images of one type objects related to one of indicated classes selected by an expert (100 images for each class). Peculiarities of lighting and spatial resolution were not considered because of the training set contains images with different lighting conditions and with different spatial resolution.

Classification of images of high spatial resolution is carried by the following algorithm (Alg 1a):

Step 1. Select next area of a source image by a "running-window".

Step 2. Build an normalized reduced histogram for chosen area for each color channel.

Step 3. Perform pixel classification by the multilayer perceptron.

Step 4. Assign a class obtained in step 3 to the point in center of "running-window".

Step 5. Form a map of morbidity rate from the obtained values of classes of objects

Classification of images of low spatial resolution is carried by the following algorithm (Alg 1b):

Step 1. Construct a mask of vegetation using features Contrast.

Step 2. If the image is processed completely, then go to step 7, otherwise choose an element from the source image by "running-window".

Step 3. If the mask of vegetation in center of the "running window" is not zero, then go to step 4, otherwise assign a point in center of the "running window" class "soil" and go to step 2.

Step 4. Build for selected "running-window" element normalized reduced histogram for each color channel.

Step 5. Perform pixel classification by the multilayer perceptron.

Step 6. Assign a point in center of "running-window" class derived in step 5.

Step 7. Form a map of morbidity rate from the obtained values of classes of objects.

Selection of image area and corresponding vegetation mask area carried out by means of "running-windows".

Figure 5 shows results of testing the algorithm. Selection of image areas was carried out by running-window of size $K\times K$ pixels without a mask (Figure 5b, 5d) and with the mask (5c, 5e) (in the experiments value K = 10 is used). The mask is formed from vegetation maps obtained using feature Contrast. In Figures 5b, 5c, 5d and 5e non classified boundary are black, soil areas are dark gray, areas with healthy plants are light gray and areas of diseased plants are white.

The results of the experiments show that the algorithms applied to RGB images are more sensitive to details that create more shallow areas classifying as "diseased plants". At the same time the details are not lost by using HSV image representation. This distinction allows obtaining maps of incidence varying detail, and thus more flexibility is appeared to recognition on the extent of diseased plants.

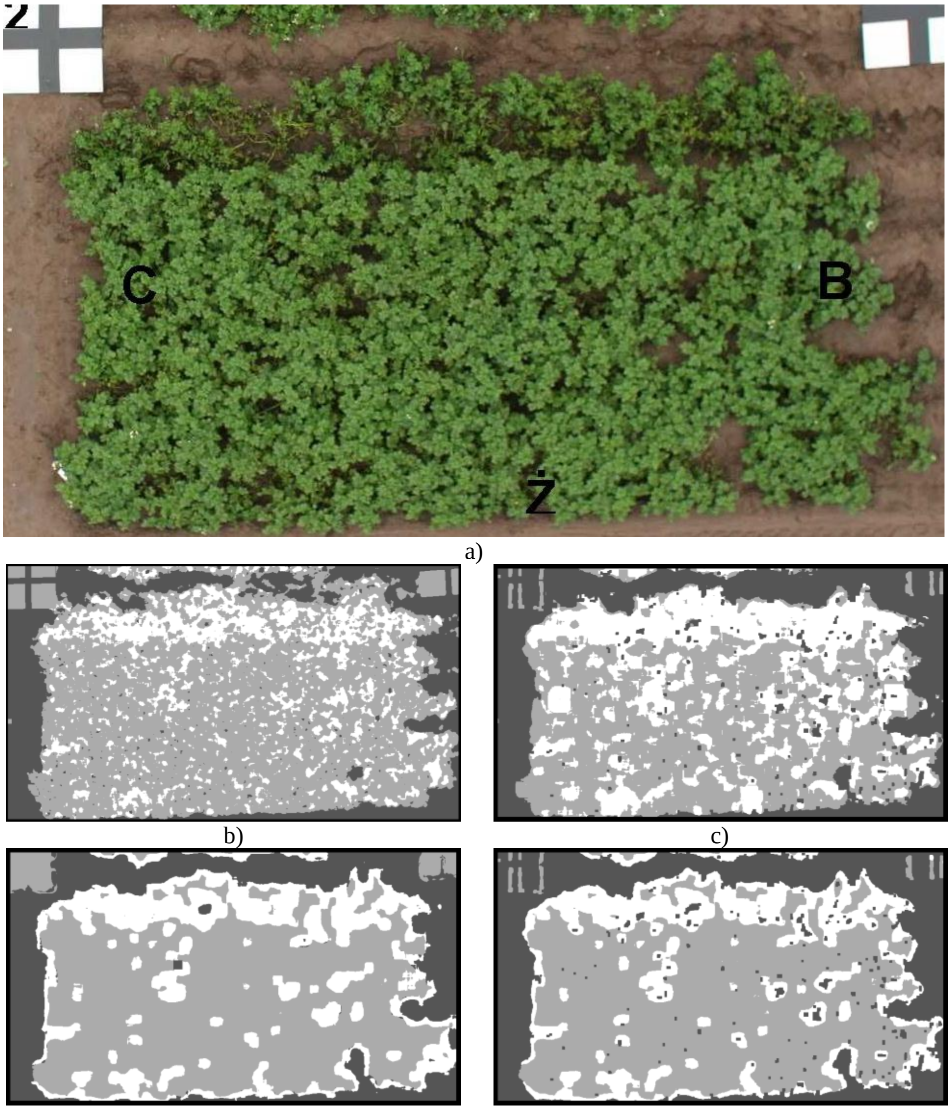


Fig. 5 Example map of disease for *K* = 10,used RGB-and HSV-submission: a) original image of a field; b) map of disease, "running-windows" without the mask (RGB); c) map of disease, "running-windows" with the mask (RGB); d) map of disease, "running-windows" without the mask (HSV); e) map of disease, "running-windows" with the mask (HSV)

3. CONSTRUCTION OF LEARNING SAMPLES

One of means to improve accuracy of neural network classification is a selection of training data. Training samples must contain a large amount of data for each object class. Reduced normalized histograms of images areas are used as data for classification. Some of these histograms are chosen to train the perceptron. Each image area can be assigned to one of three classes: "healthy vegetation", "diseased vegetation" and "soil". A histogram type is dependent on content of an initial image area and image resolution. An area selection in a training set is based on an experience of an expert who constructs the training set. Thus, classification quality dependence on image resolution of the training sets should be examined. The obtained information is advisory in nature and can be considered by the expert as needed.

A research of the quality classification dependence is based on three training sets containing:

- both high and low image resolution areas;
- only low image resolution areas;
- only high image resolution areas.

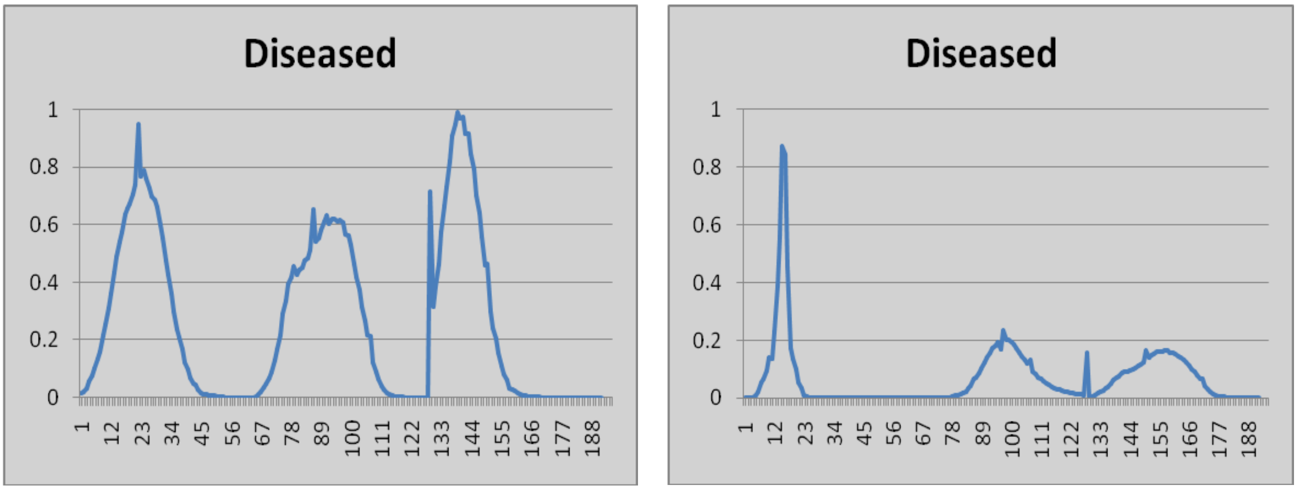
The all were are used for training a multilayer perceptron. Further a classification was carried out on the initial image for different sizes of “running windows”: $K = 10$, $K = 20$ and $K = 30$. The obtained classification results (for class “disease affected plants”) were compared pixel by pixel with a disease map formed by an expert. The number of different pixels characterizes an error. Table 1 shows results of tests of the quality classification dependence on areas dimension of the training image set.

Figure 6 shows the reduced normalized histograms prepared in color space HSV for both low (Fig. 6a) and high (Fig. 6b) image resolution areas containing disease affected plants.

4. CONCLUSIONS

The analyses of a problem of special areas detection and recognition on agricultural fields images reveals a lack of methods and algorithms for selection and classification of areal objects in multi-temporal images of agricultural fields with different spatial resolution. To solve this problem, analysis of subject area is carried out. As result it was found that direct application of any of existing methods do not provide full solution of the problem of detection and land cover classification of agricultural fields using multi-temporal data.

Neural network algorithms for object classification are proposed in the paper. To solve the problem of agricultural field images classification, analysis of crop plants images color features is carried out. The analysis of aerial photographs of agricultural fields is based on an analysis of photographs of individual plants. As a result, it has been determined color characteristics of various diseases, as well as a number of features that are present in images, which can affect quality of classification.



a) b)

Fig. 6 – An example of the reduced normalized histograms in color space HSV: a) for low image resolution area; b) for high image resolution area.

Table 1 – Tests results.

HSV				
Resolution	**Training epochs**	**Error**		
		***K*=10**	***K*=20**	***K*=30**
Low + High	32	16.888	21.650	24.996
Low	22	16.050	16.178	15.351
High	46	16.837	17.684	18.021
RGB				
Resolution	**Training epochs**	**Error**		
		***K*=10**	***K*=20**	***K*=30**
Low + High	61	20.028	23.155	24.150
Low	50	44.293	39.371	29.738
High	84	26.242	23.840	20.881

The algorithms of constructing of reduced normalized histograms (using RGB and HSV-view of images), and classification algorithms based on using of color features represented in form of reduced normalized histograms, and taking into account spatial resolution of source images are proposed.

The practical importance consists of application of the developed algorithms for natural origin objects allocation that allow increasing essentially accuracy and reliability of functioning of computer vision systems, monitoring and decision-making.

Possible area of application is remote sensing of the Earth (in forestry, geology, agriculture).

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