Analyzing Digital Image Processing Capabilities while Growing Crops

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Abstract. Global technological development in the world has created new competitive conditions for farmers. Therefore, today cultivation of different crops cannot be imagined without modern means of control and processing of biometric information about the plant. Data that serve as criteria for evaluating such information include a number of visual and biological attributes. If the biological signs of plant diseases cannot be determined without special analyzes, then the visuals are effectively captured by digital imaging tools. In addition, carrying out special biological analyzes is a rather painstaking and complicated procedure, which requires not only time but also considerable resources. And the most important problem in such studies can be considered the inability to grasp the entire acreage of plants, if not separate miniature greenhouse complexes. In contrast to biological assessment of the condition of plants, visual gives a number of advantages in the cost of such studies, the speed of their conduct, and the ability to reach the entire acreage. However, the disadvantage of this approach is the quality of plant evaluation, which depends primarily on digital imaging technologies, the correctness of the application of an algorithm for recognizing a particular disease, the effectiveness of video surveillance hardware and the speed of transmission of digital images. Therefore, it is precisely the methods and tools for digital image processing that are the subject of research in this work, and also have a high relevance in the agro-industrial field.

Keywords: image recognition, plant disease, machine vision.

1 Introduction

Today, image processing is an effective tool for analyzing the state of plants in various fields of agriculture. Visual analysis techniques such as thermal imaging, hyperspectral imaging, photometric imaging and others based on image research have made

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a significant contribution to the technological development of agriculture and have fully justified their purpose. The image analysis process has the following steps:

1. Determining the features of the image, characterized by certain points that can be explored by the use of special filters;
2. Establishment of their coordinates for further diagnostics;
3. Identification of the features of these points for their identification.

All this allows us to recognize certain plant diseases with a high degree of accuracy, namely:

1. Find the site of plant disease;
2. Quantify the degree of its development;
3. To examine the affected area for features of the disease;
4. Determine the size of the plant itself.

As a result of this analysis, you can determine the methods of crop management, detect the presence of weeds, estimate the required amount of nutrients to improve plant growth, etc.

Therefore, image analysis can be considered as an effective tool for non-destructive means of identifying plant diseases.

The analysis showed that image recognition algorithms such as: SIFT; SURF; ORB; FAST; PCA-SIFT; F-SIFT are popular today.

Thanks to these algorithms, it is possible to define special points in the image and set their descriptors, which are quantitative characteristics of the neighborhood of special points, which are laid out in a certain sequence. Such a sequence is called the histogram of descriptors.

2 Literature Analysis and Problem Statement

As a result of the analysis of the literature, it is determined that these algorithms are widely used in agriculture, but each has individual features [1-4]. They are in the ratio of the received descriptors. Yes, some can be used in invariance of the image to scale and size, but at the same time have a considerable load on the computer system, others are not resistant to invariance, but fast in implementation. In general, there is no one-size-fits-all approach to image recognition, each algorithm can be applied to different tasks separately.

The vast majority of works describing the possibility of using machine vision in agriculture characterize the methods of detection of plant diseases by such criteria as the characteristics of the color of the plant [5] and features of the structure of their leaves [6]. However, a more logical and effective way is to combine these approaches into one.

In practice, tasks that are related to the recognition of features of a certain size (recognition of plant defects) are often encountered. Therefore, in solving such problems, the features of the image processed by the numerical matrix [7] are established in order to determine local characteristics. In such circumstances, the construction of an algorithm for the diagnosis of plant diseases faces a considerable number of computational difficulties. This is due to the need to process large data sets.

No less important obstacle to the identification of plant disease by color is the noise generated by the camera flash or the change in light and many other factors. For this purpose, scientists apply different filters [8]. Depending on the plant and the features of the images, they try to find the optimal filter. For example, in [9], for the detection of rice diseases, it was proposed to use the Otsu method, which enables the use of low-pass filters to reduce unnecessary noise.

In order to identify spots that are poorly visible and which are signs of plant disease, a filter was used in [10] to smooth the image, in order to further identify the edges of the image.

In order to identify the maximum number of criteria for plant disease on a digital image, it requires multistage processing. So, to identify the color signs of the disease use filters of a certain color. However, the color of most plants is heterogeneous. Therefore, if it is simply formalized by a single number (for example, the mean), it is unlikely that this feature will be selective. Therefore, some researchers, to increase the saturation of the hue, first convert the RGB image classification to HSV. After that, the separation of color clusters that characterize the affected area of the plant is used [11]. Others convert RGB images to YCbCr, which also produces good results [8].

Then, to reduce unnecessary noise, a low-pass and high-pass filter is smoothed out, giving a clearer image structure. After that, painful spots are identified. Applying this stage of identification can determine a significant percentage of the disease, but this is not sufficient, because in addition to the color shades, the plant also has specific forms of painful spots (Fig. 1). And their accurate detection can greatly increase the accuracy of diagnosis.

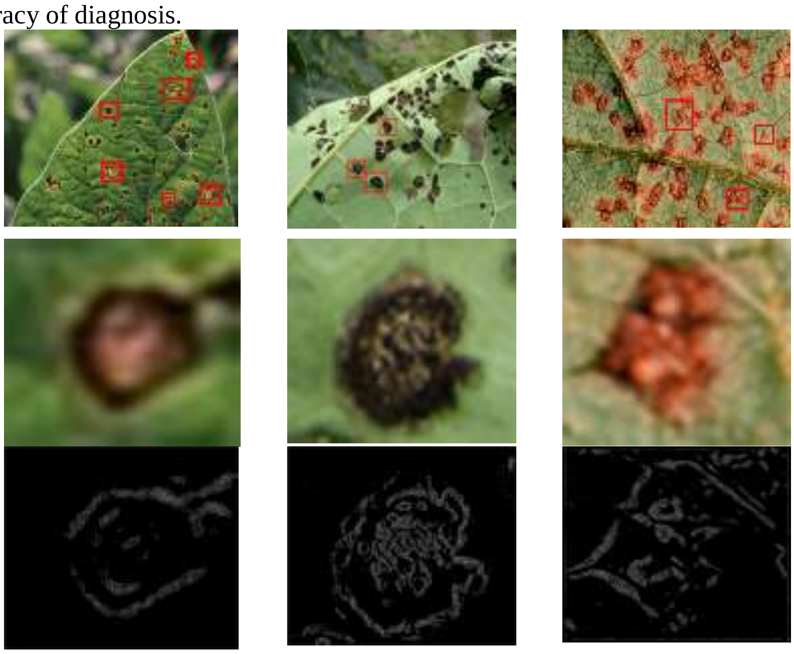

Fig. 1. Visual features of plant diseases

The figure shows the originals of images that have signs of disease-leaves. Their contours are highlighted using the Kenny operator [12]. These spots have special points that can be identified by the detectors mentioned in the article.

To select the most effective detectors, they should be classified by category.

The aim of this study is to study the characteristics of popular spot and color detectors using plant disease identification.

Such a goal can be achieved by statistically examining the results of the identification of plant diseases, using the detectors mentioned in the article, by determining the most optimal result.

3 Ways to identify plant diseases based on color spectrum filters and special points

For the initial identification of the disease of the plant, the most pronounced sign can be considered a color change on its outer parts (leaves, stem, fruits).

The first step to determine the color features of a plant disease is the need to filter out noise in the image by smoothing its histogram. The color spectrum is then filtered. For example, in the HSV color space, given the saturation.

As a result of color filtering, it is necessary to highlight the specified range of a given color spectrum and to set specific points on it, which must be invariant to scale and transformation.

The part of the image thus obtained can be examined by its shape and external features. Special point detectors must be used for this purpose.

The use of special point detectors on selected parts of the image has some difficulties because they have different clusters and different scales. However, the spots have some similarities.

Therefore, edge detectors can be used to identify such pain spots. To reduce unnecessary noise, filters are used.

Today, the Kenney filter has become widely used for image border detection. The principle of its action is as follows [13]:

1. Noise smoothing is performed;
2. The gradient analysis method is applied. With respect to the intensity of the color change, image contours are determined, highlighting only local maxima;
3. Boundaries are determined by suppressing edges that are not connected to the main boundaries.

Painful spots, as noted above, have similar features. To distinguish them more clearly, we apply the Gauss method. The kernel of this filter is expressed by the formula:

$$\mathrm{F}_{\mathrm{gauss}}(\mathrm{i},\mathrm{j}) = \frac{1}{2\pi\sigma^2\lambda}\exp\left(-\frac{i^2-j^2}{2\sigma^2}\right), \tag{1}$$

where:

i, *j* are the pixel coordinates of the image;

σ is noise.

Thus, using this filter, it is possible to blur the noise. Noises are an obstacle to discover the unique features of the plant's painful spots.

The last step to double identifying painful spots is to use the detector of special points that are difficult to isolate, due to changes in lighting and tilting of the camera. However, if you look at a particular plant disease, you may find that its visual characteristics have some similarity.

The most well-known detectors used today to solve such problems include SIFT, SURF and ORB.

The SIFT detector [14] includes two main steps, which are to determine the specific points in the image that are invariant to scale and rotation. And also, to further correlate them with other images, it is necessary to define the descriptors of such points.

The first stage is implemented using the Gaussian Pyramid, as well as the Difference of Gaussian (DoG).

Gaussian is considered an image that is blurred by a Gaussian filter.

$$\mathrm{L}(\mathrm{x},\mathrm{y},\sigma)=\mathrm{L}(\mathrm{x},\mathrm{y},\sigma)*\mathrm{L}(\mathrm{x},\mathrm{y}), \tag{2}$$

where:

L is the Gaussian value at the point with coordinates (x, y);

Σ is blur radius;

G is a Gaussian kernel;

I is the value of the original image;

* - convolution operation.

In this case, the difference is called the Gaussians image obtained by subtracting each pixel of one Gaussian source image from a Gaussian with a different blur radius.

$$\begin{aligned}&\mathrm{D}(\mathrm{x},\mathrm{y},\sigma)=(\mathrm{G}(\mathrm{x},\mathrm{y},\mathrm{k}\sigma)-\mathrm{G}(\mathrm{x},\mathrm{y},\sigma))*I(x,y)=\\&=\mathrm{L}(\mathrm{x},\mathrm{y},\mathrm{k}\sigma)-\mathrm{L}(\mathrm{x},\mathrm{y},\sigma),\end{aligned} \tag{3}$$

To determine the special point, together with the construction of the Gaussians pyramid, a pyramid of differences of Gaussians is constructed, consisting of differences of neighboring images in the pyramid of Gaussians. Accordingly, the number of images in this pyramid will be $N + 1$.

After constructing the pyramids, a point can be considered special if it is local to the extremes of the Gaussians difference.

The refinement of singular points is achieved by approximating the DoG function by the second-order Taylor polynomial taken at the point of the determined extremum.

After refinement, based on the neighborhood of the singular point, a descriptor is constructed, which can be represented as a gradient matrix by each pixel surrounding the singular point.

The result of constructing such a matrix is to create a histogram of the descriptor, which is used to further correlate the image with others.

SIFT detectors are most recommended for feature matching in images [15]. But to increase the speed of calculation, if necessary, fast detectors such as SURF are used.

SURF has a performance close to SIFT. Although studies have shown that when speed is not a critical factor, SIFT is superior to SURF [16]. Thus, the SURF method uses the Hessian matrix to find the singular points, whose determinant reaches the extremum at the points of maximum change in the brightness gradient.

For example, the original image is given by the intensity matrix I. The current pixel, which is analyzed for color intensity change, can be denoted by X = (x, y). Scale of the filter σ. Then the Hessian matrix will look like this:

$$\mathrm{H}(\mathrm{x},\sigma)=\begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix}, \tag{4}$$

where: $L_{xx}(x,\sigma), L_{xy}(x,\sigma), L_{yy}(x,\sigma)$ are convolutions of the approximation of the second Gaussian kernel derivative with image I.

Thus, the determinant of the Hessian matrix reaches the extremum at the points of maximum change in the brightness gradient.

The SURF method uses a Gaussian kernel filter throughout the image, finding specific points at which the maximum determinant of the Hessian matrix is reached. Thanks to this search, both dark spots on a white background and vice versa stand out.

Unlike SIFT, the SURF method, without checking the accuracy of the points found, immediately generates descriptors.

SURF is a set of 64 numbers for each key point, which, unlike SIFT (128 numbers), has a smaller dimension. Just like SIFT, SURF is invariant to rotation and scale.

The ORB method, for finding key points, determines the intensity limit between the center pixel and the circle described around it.

Once specific points have been identified, an Harris angle detector is used to refine them [17].

To obtain N key points, the first step uses a low threshold. This is done in order to get more special points N. They are then sorted using the Harris metric. In this case, the first N points are selected.

ORB is also invariant to rotation by constructing a descriptor of points obtained based on the BRIEF modification [18].

Considering the capabilities of special spot detectors in images, color isolation methods, smoothing techniques and edge detectors, one can construct an algorithm for identifying plant diseases as follows [19-21]:

1. Receiving an RGB image from the video camera;
2. Converting an array of image points into an HSV array to set the boundaries of the color spectrum of painful spots depending on the color gamut range;
3. Separation of a painful spot by its color characteristics from other points of the image
4. Allocation of borders of painful spots that occur on the centers of the disease;
5. Noise-smoothing in order to distinguish clear forms of such area;
6. Finding special points and their descriptors;
7. Comparison of descriptors with descriptors found in other images on the relevant signs of plant disease.

4 Digital image processing to determine the features of plant diseases (for example, red currant disease)

To solve the problem of identifying the disease of red currant by machine method, visual signs of individual painful spots are needed. Let it be the leaves of a plant that shows signs of disease that have a specific color (Fig. 2).

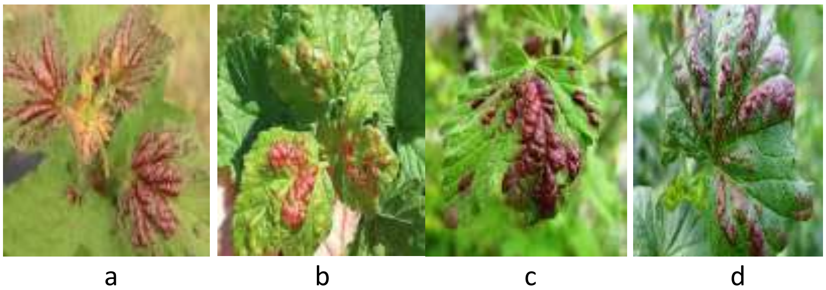

Fig. 2. Signs of red currant disease

To determine the color range by which individual points of the image characterizing the currant disease cell will be highlighted, the color spectrum range is set. In order to increase the spectrum, it is necessary to convert the RGB format to HSV. In this case, color low = (4,73,47), color high = (18,255,200) in HSV format. Then we separate the points that are in this range and get the area of characteristic signs of the disease.

To establish the specific contours of this area, we will use the Kenny Border Detector. Then, after low- and high-frequency filtration with a Gaussian filter, we get a smoothed image that more clearly reflects the unique signs of the disease.

The software implementation was performed using the OpenCv library in Python programming language.

Thus, filtered areas of red currant disease have the following form. (Fig. 3.)

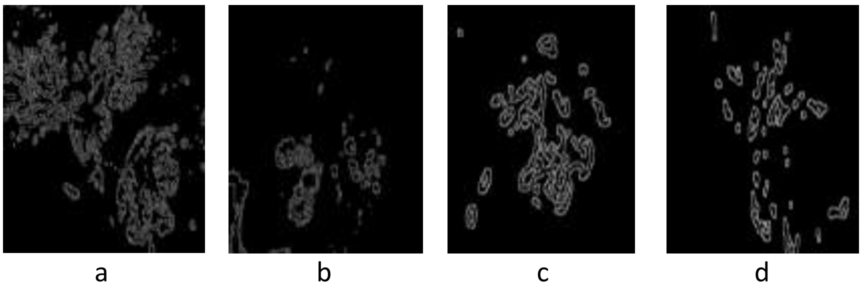

Fig. 3. Identified signs of red currant disease after treatment with color filters, edge detector and Gaussian filter

Natural peculiarities of painful spots, have certain protuberances. As can be seen in the figure, after filtration, they stand out in the form of similar ellipses. Their difference lies in scale and location.

Based on such forms, we apply to the determination of their uniqueness SIFT and SURF detectors, which are invariant to scale and rotation. After receiving the special points, we fix their number, determine the number of similar descriptors with the sample image (Fig.4 b), and fix the processing time for each of the detectors (Tab. 1).

a b

Fig. 4. Sample of sick red currant leaves

As a result of the study, one can observe a higher speed of operation of the SURF detector compared to SIFT. However, the efficiency of SIFT is twice the number of descriptors found.

Table 1. The result of image processing using SIFT and SURF detectors.

Detector	**SIFT**				**SURF**			
Number of special points in images a, b, c, d Fig. 3	a 4663	b 1907	c 554	d 424	a 2023	b 980	c 244	d 167
Image Size (pixel)	600×450	769×577	233×216	284×177	600×450	769×577	233×216	284×177
Processing time (seconds)	2.019	1.494	0.546	0.485	1.039	0.762	0.232	0.179
Number of similar descriptors with reference image (Fig. 4 b)	178	193	252	203	63	87	93	104
Percentage of similar descriptors with reference image, (%)	3,8	10,1	45,5	47,9	3,1	8,9	38,1	62,3

Some images, such as Fig. 3, d have the highest number of similar descriptors when correlated with the image descriptors Figs. 4. This is due to the fact that the structure of the painful spot on the leaves of red currant consists of elliptical forms, which are most clearly expressed in Fig. 3, d. Such elliptical shapes determine the detectors in the process of image correlation. The average percentage of similar descriptors with the comparative image (Fig. 4 b) using the SIFT detector is 27%, SURF - 28%.

5 Conclusion

Analysis of digital imaging methods in agriculture has shown the high relevance of the development of machine vision technology. However, the large number of recognition errors is a major drawback [22-25]. The considered example of double identification of the affected area of the diseased plant, using color spectrum detectors, as well as special point detectors, was proposed in order to increase the identification accuracy of a single part of the image. As a result, it has been found that the SIFT detector is the most optimal for determining special points in the image, but it requires considerable computing power, which is proved during the experiment. The SURF detector showed faster action, but the number of special points found on the images under study was less than twice that of the SIFT detector.

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