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Creation and Study of 3D Models for Digital Plant Phenotyping

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Abstract—In this article, the authors present the results of the development and study of methods for creating 3D models of plants grown in vitro, which provides the ability to accurately record the morphometric indicators of the growth of the individual parts and organs of plants, as well as of plants as a whole, cultivated on different nutrient media. The presented methods and algorithms together solve the problems arising in the process of studying plants in a test tube, such as those related to the complexity of the plant structure, the occurrence of distortions at the borders of the test tube, fogging of the test tube, and the influence of the human factor. A bank of 792 3D models has been created for plants of six species, allowing simulation experiments to be conducted to identify cause-and-effect relationships, forecasting and gaining new knowledge. The developed methods have been checked for adequacy, and an example of use for a specific plant is presented. The presented methods and algorithms can be the basis for the implementation of the process of digital phenotyping of plants.

Keywords: in vitro conditions, methods, algorithms, 3D modeling, segmentation, digital phenotyping

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INTRODUCTION

The present time is characterized by a deep penetration of digital technologies and automation tools for use in conducting interdisciplinary research to gain new knowledge of processes, objects, or phenomena under study.

Thus, microclonal propagation of plants (a vegetative method of plant propagation using in vitro technology), a promising biotechnological process, provides the possibility of obtaining genetically homogeneous planting material without bacterial and fungal infections; reduces the duration of the selection process; makes it possible to reproduce rare and difficult-to-cultivate plants by traditional methods; and ensures a high rate of reproduction. However, to accelerate reproduction and obtain high-quality planting material under in vitro conditions, it is necessary to select the optimal composition of nutrient media and environmental parameters at each stage of plant development individually for each culture and even for individual varieties. This requires accurate registration of morphometric indicators of the growth of individual parts, plant organs, and plants in general, cultivated in different nutrient media, which is associated with the need for objective registration and simultaneous processing of a large amount of data, reducing the influence of the human factor. This problematic task can be solved using digital phenotyping using the construction and analysis of 3D plant models [1–3].

1. FORMULATION OF THE PROBLEM

The morphometric parameters of plants can be estimated on the basis of two-dimensional images or of their volumetric reconstruction in three-dimensional space [4]. In the first case, measurements are made in the image plane in pixels, which are further converted to the metric system [5–7]. This approach has algorithmic and computational simplicity relative to methods that work with 3D plant models, and it is capable of producing a very accurate estimation of the parameters of plants with a relatively simple anatomical structure. The disadvantages of the method appear as the anatomical structure of the plant becomes more complex. Thus, a large number of leaves or with large leaf plates can hide the elements of the plant located behind them, thereby making it impossible to correctly assess its structure. To overcome this problem, a series of photographs from different angles is used: a top view with a series of side views with a fixed rotation step. On each image, the parameters are calculated, and then the obtained values are analyzed in order to obtain the most reliable ones [8]. However, even with this approach, it is impossible to obtain many parameters with high accuracy, such as leaf angles, surface areas, and leaf and stem volumes.

The automated creation of an accurate volumetric reconstruction of plants with a complex structure consisting of tens and hundreds of leaves of arbitrary shape located at different angles has long been an unsolved problem. Nowadays, using high performance computers, portable cameras, and sensors, it has become possible to apply many approaches to create an accurate 3D model of plants. An essential feature of the study of plants in vitro should be noted. Optical cameras make it possible to obtain images of a plant behind glass, thereby not disturbing the microclimate of the test tube and without injuring the plant. However, the resulting images may have various distortions caused by fogging and glass defects, nonlinearities at the boundaries of the test tube, and the glare and reflections of surrounding objects. In the process of creating a 3D model of a plant, it is necessary to take into account possible distortions and, if possible, compensate for them. Let us consider some approaches.

There are many methods for creating a 3D model from 2D images. These methods are united in foreign literature by the term "Shape from X," where X indicates what the method itself is based on [9]. We consider the family and principles of operation of such methods.

Shape from Shading: Create a 3D model from a single image based on brightness analysis. This method creates a volumetric reconstruction of an object from a single image in grayscale based on the analysis of changes in brightness using the Lambert model [10]. The Lambert scattering model defines the function of the dependence of the brightness of an image point on the intensity of the light source, the reflectance of the surface albedo, and the scalar product of the unit normal to the surface and the vector directed to the light source.

The disadvantages of this approach are the need to initially set the parameters of the scattering law, as well as significant assumptions in assessing the reflective properties of the surface, which leads to inaccuracies in the volumetric reconstruction of the object.

Shape from Silhouette: creates a 3D model based on the silhouette of an object in an image. The method creates a three-dimensional model in the form of a convex surface of an object based on image silhouettes by comparing them at different angles [11]. Increasing the number of input object silhouettes obtained from images increases the accuracy of the resulting model. The complication of the geometry of the modeled object significantly reduces the accuracy of the resulting model. The Shape from Silhouette method is quite simple to implement and only requires a series of images taken from different angles with known camera positions. The greatest complexity of the method lies in the segmentation of the silhouette of the object under study in the image, which can be a laborious task in the natural environment, but in laboratory conditions, it can be easily solved by placing the object against a uniform background.

Shape from Stereo: creates a 3D model from a stereopair can be performed using methods based on the search and processing of special points, or areas, or a combination of them. Methods based on the search and processing of singular points search for local features in each image and search for correspondences between the points of a pair of images. For matched points on a pair of images, the distances are calculated by triangulation. Distances for all other points are calculated using interpolation. Methods based on the search and processing of areas are used to calculate the distances to all points in the image. The combination of the first and second methods was described in Bernard's algorithm [12], which uses a displacement map based on the calculation of the displacement at each point of the image.

The disadvantage of this algorithm is a significant loss in accuracy with insufficient information about the spatial structure of the object [13].

Shape from Motion: creates a 3D model from a set of images taken while the observer is moving. This method creates a volumetric reconstruction of an object from a series of images obtained at different camera positions relative to the object, where the precise position of the camera and its internal parameters may not be known. The method consists of two main steps. The first one searches for local features in each image and correlates the found features in a series of images. At the second step, for the found correspondences, the position in three-dimensional space is determined using the triangulation method. Polygons are superimposed on the obtained points in three-dimensional space and make up the polygonal surface of the object [14]. The disadvantage of this method is the need for the object under study to have a non-uniform surface texture for a clear definition of a large number of singular points and lines.

The revealed shortcomings of the existing methods of phenotyping do not allow their use for obtaining and analyzing the morphometric parameters of plants in vitro, which necessitates the development of a new approach presented by the authors.

The authors set the task of developing methods and algorithms for determining the morphometric characteristics of plants based on a 3D model of the test sample, the complex of which will allow for the first time the automatic creation of the entire required comprehensive list of parameters of the vegetative part of the plant in vitro, without disturbing the microclimate inside the test tube.

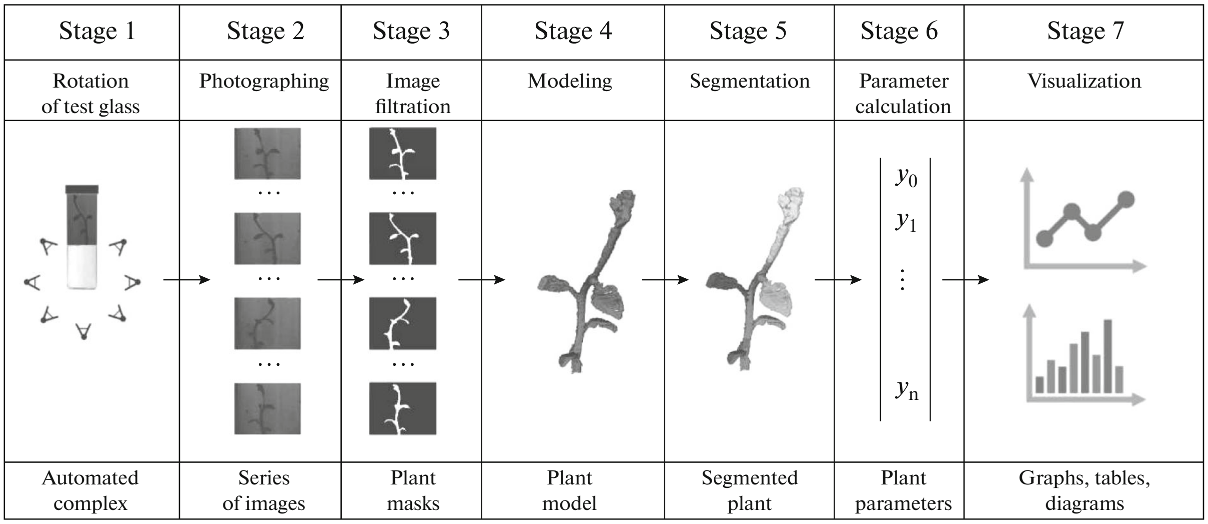


Fig. 1. Stages of the ASNI work in the field of the micropropagation of plants.

2. STAGES OF OPERATION OF THE SOFTWARE AND HARDWARE COMPLEX

To solve this problem, the authors have developed a software and hardware complex, the process of which consists of seven main stages: (1) placement of a test tube with a plant in an automated digital phenotyping system; (2) obtaining photographs of the plant in the required angles and spectra; (3) processing of the obtained images in order to highlight the plant against the background and obtain bit masks; (4) building a 3D model of a plant; (5) segmentation of the 3D model into organs; (6) calculation of the required parameters for the obtained segments; and (7) visualization of the received data to the user (Fig. 1).

3. PLANT SEGMENTATION METHOD IN IMAGES

In the first stages, the test tube is rotated and photographs of the plant are collected from various angles. After taking photographs of the plant in the required angles, it is necessary to select the bit masks of the plant, which are necessary to create a 3D model. A method for segmenting plants in images was developed. Approaches were tested using classical computer vision methods, as well as based on machine learning. When using an approach based on classical computer vision methods, two main drawbacks were identified: (1) the plant segments qualitatively in the center of the test tube, but loses a lot of accuracy at the boundaries of the test tube and the nutrient medium, due to an increase in the number of false positive pixels or pixels erroneously assigned to the area of the plant; (2) when condensation appears inside the test tube, drops on the walls significantly distort the color space of objects located behind, as a result of which the number of false negative pixels increases. or pixels that are erroneously not assigned to the plant area.

For plant segmentation by machine learning methods, a segmenting neural network with the U2-Net architecture was used. The architecture of this neural network is able to solve the above disadvantages of classical methods, and it is also distinguished by the ability to learn on a small sample and is known for its speed. This approach makes it possible to significantly reduce the number of voids inside the contours of plants that occur during segmentation using classical computer vision methods due to the presence of condensate on the walls of the test tube.

Examples of image segmentation with plants using a neural network with U2-Net architecture are shown in Table 1, where CV* is a bitmask obtained using classical computer vision methods, NN** is a bitmask obtained using a neural network, and GT*** is a bitmask marked manually.

The results of the precision, recall, and F1 metrics obtained using both methods were compared (Table 2). The advantage of the method using machine learning is revealed.

4. CONSTRUCTION OF 3D MODELS AND SEGMENTATION OF MODELS INTO ORGANS

The construction of a 3D model based on a series of images is performed using the iterative Space Carving method with additional allowances for the input parameters of the allowable error during reconstruction hh_3. This parameter allows voxels to be included in the model projected onto images with a plant, provided that the voxel box projected onto the image has at least one non-zero pixel on at least $n - \mathrm{thresh}_{3D}$ images where n is the number of processed images.

Table 1. Visualization of the iterative process in the segmentation of images with plants

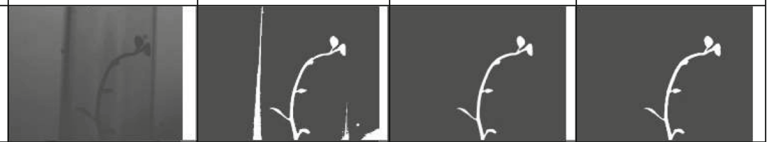
N	Original image	CV*	NN**	GT**
1				
2				
3				
4				
5				

Table 2. Comparison of methods for segmenting plants in an image

An approach	Precision	Recall	F1	FP	TP	FN
CV	0.497	0.767	0.603	4773417	4724341	1436863
NN	0.951	0.917	0.933	248585	4835602	440389

Thus, the problem of the presence of various distortions in images caused by fogging and defects in the glass of the tube, nonlinearities at the boundaries of the tube, and glare and reflections of surrounding objects is partially solved.

For the resulting plant model, segmentation into organs, that is, the stem and leaves, is performed. The algorithm for this process is shown in Fig. 2. A plant graph is built according to a 3D model, the base vertex of the stem is determined, and segments are iteratively identified, consisting of the shortest path from the beginning to the end of the segment and the vertices belonging to this path, and the class of the segment is determined.

A method for determining the morphometric features of the test sample is developed. In total, 10 plant parameters are taken into account, namely, its volume; the coordinates of the start point; coordinates of the end point; the height, length, and surface area of the plant or its parts; the maximum and average width; and the azimuth and slope of plant parts. The volume of a plant or its parts is determined by raising the product of the number of voxels of a single segment and the voxel size to the third power:

$$\text{Volume}_i = n_{\text{item}_i} v_{\text{base\_size}}^3,$$

where n_{item_i} is the number of voxels in a single segment or in the plant model as a whole, and $v_{\text{base\_size}}$ is the voxel size.

The coordinates of the start point of the plant or its parts correspond to the first element in the shortest path s_{path_i}:

$$p_{\text{base}_i} = s_{\text{path}_i}[0].$$

The coordinates of the end point of the plant or its parts correspond to the last element in the shortest path s_{path_i}:

$$p_{\text{end}_i} = s_{\text{path}_i}[-1].$$

The height of a plant or its parts is defined as the difference between the maximum and minimum value of the coordinate z V s_{path_i}:

$$\text{height}_i = \max\left(s_{\text{path}_i}[:]['z']\right) - \min\left(s_{\text{path}_i}[:]['z']\right).$$

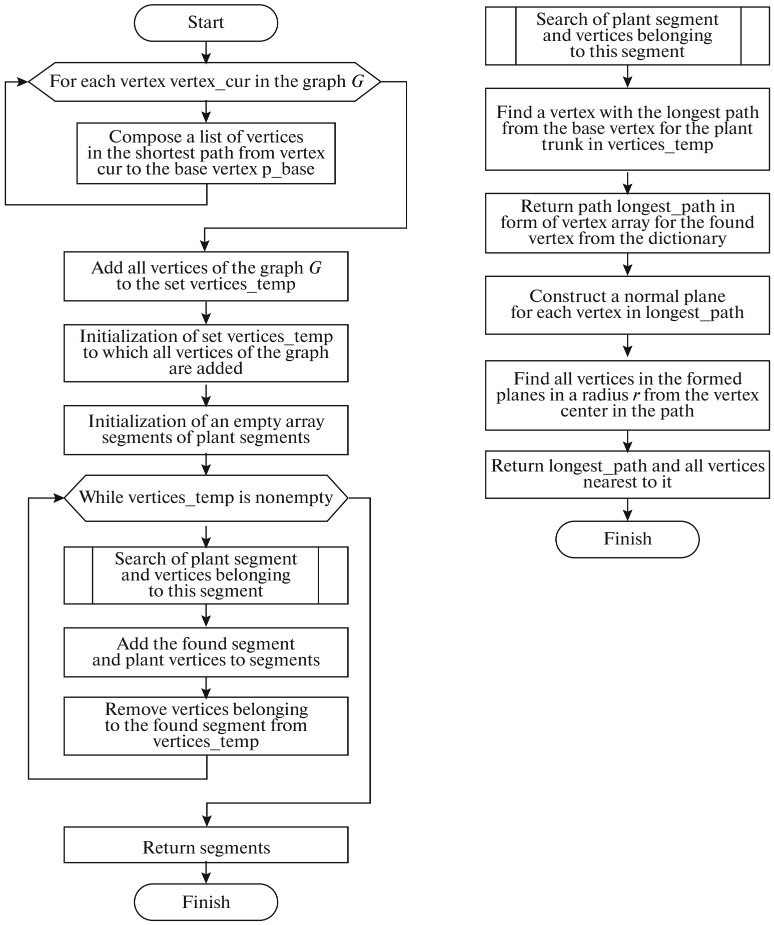


Fig. 2. Algorithm for implementing the method of plant graph segmentation into elements.

The length of a plant or its parts is defined as the sum of the Euclidean distances between consecutively connected vertices of the shortest path $_h$ from the two most distant points of the segment:

$$\mathrm{length}_{\mathrm{slices}_i} = \begin{vmatrix} \left\|\overrightarrow{V_0V_1}\right\| \\ \left\|\overrightarrow{V_1V_2}\right\| \\ \cdots \\ \left\|\overrightarrow{V_{j-1}V_j}\right\| \end{vmatrix}; \quad \mathrm{length}_i = \mathrm{sum}\left(\mathrm{length}_{\mathrm{slices}_i}\right).$$

The maximum width of a plant part is defined as the maximum value in the vector

$$\mathrm{width}_{\mathrm{slices}_i} = \begin{vmatrix} \max\left(v^2_{0_{\mathrm{neighbor}_i}} - v^2_{0_{\mathrm{neighbor}_j}}\right)^{\frac{1}{2}} \\ \max\left(v^2_{1_{\mathrm{neighbor}_i}} - v^2_{1_{\mathrm{neighbor}_j}}\right)^{\frac{1}{2}} \\ \cdots \\ \max\left(v^2_{n_{neighbor_i}} - v^2_{n_{\mathrm{neighbor}_j}}\right)^{\frac{1}{2}} \end{vmatrix},$$

$$\mathrm{width}_{\max_i} = \max\left(\mathrm{width}_{\mathrm{slices}_i}\right).$$

The average width of plant parts is calculated as the sum of all elements of the vector *width_slices* divided by their number:

$$\mathrm{width}_{\mathrm{avg}_i} = \frac{\sum_{j=1}^{N} \mathrm{width}_{\mathrm{slices}_{i,j}}}{N}.$$

To calculate the leaf area, any of the numerical integration methods is used for h at intervals h. The double value of the integral is the surface area of the sheet on both sides:

$$\mathrm{area}_{\mathrm{leaf}_i} = 2\int_0^N f_{\mathrm{leaf}_i}(x)\,dx.$$

To calculate the area of the plant stem, we represent the stem as series-connected cylinders and add the areas of their lateral surfaces:

$$\mathrm{area}_{\mathrm{stem}} = \pi\left|\mathrm{width}_{\mathrm{slices}_i}\right|^T \left|\mathrm{length}_{\mathrm{slices}_i}\right|.$$

The surface area of the whole plant is the sum of the surface areas of the leaves and the stem:

Table 3. Plant segmentation quality metrics by species and on average

Plant	MAE	MSE	MAPE	MPE
Ficus lyrata	0.785	1.785	0.077	0.0178
Anubias congensis	0.167	0.167	0.017	0.017
Erysimum asperum	0.333	0.333	0.055	0.055
Secale cereale	0.417	0.583	0.089	0.035
Pisum sativum	0	0	0	0
Campanula persicifolia	0	0	0	0
Average	0.298	0.514	0.041	0.003

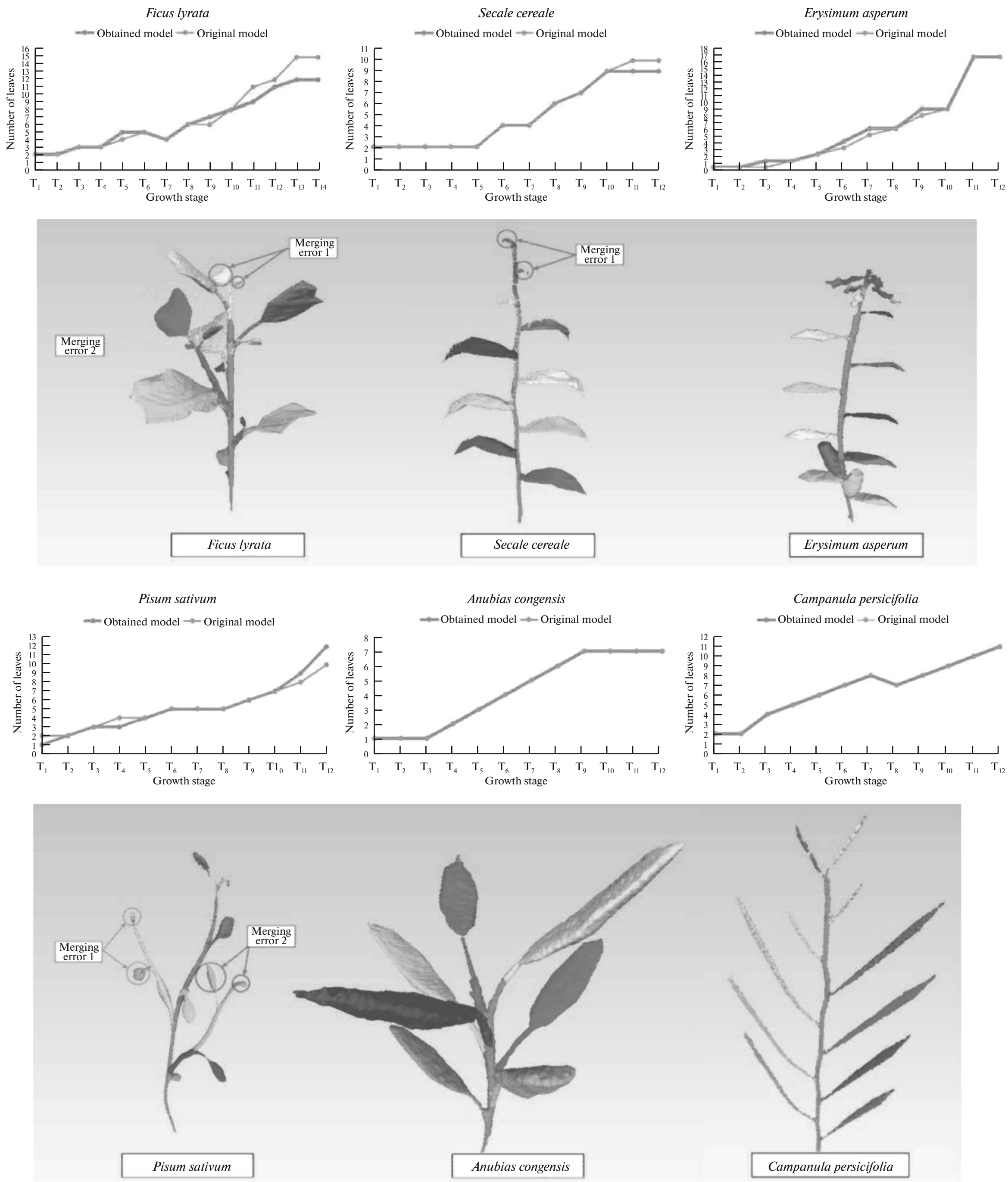


Fig. 3. Graphs of the number of leaves in the process of growth in T_1–T_n plants.

$$\text{area}_{\text{plant}} = \text{area}_{\text{stem}} + \sum_{i=1}^{N} \text{area}_{\text{leaf}_i}.$$

The azimuth of plant elements is calculated as arc tangents from the y and x projections of the mean value of the sum of vectors along the shortest path $_h$ from the two most distant points in the segment:

$$v_{\text{mean}_i} = \frac{\sum_{j=1}^{N} v_j - v_{j-1}}{N}; \quad \text{azimuth}_i = \arctan \frac{v_{\text{mean}_i}[1]}{v_{\text{mean}_i}[0]}.$$

The inclination of plant elements relative to the vertical axis is calculated as the average value of the sum of scalar products between the normalized values of the vectors in $_h$ and unit vector$\hat{}_0$, directed along the 0Z axis:

$$\text{tilt}_i = \frac{\sum_{j=1}^{N} \arccos \frac{\left(\widehat{v_j - v_{j-1}}, \widehat{v_{0Z}}\right)}{\left|\widehat{v_j - v_{j-1}}\right| \left|\widehat{v_{0Z}}\right|}}{N}, \quad \widehat{v_{0Z}} = [0,0,1].$$

A knowledge base was formed, including 792 units of a 3D model of plants of six species: *Ficus lyrata*, *Anubias congensis*, *Erysimum asperum*, *Secale cereale*, *Pisum sativum*, and *Campanula persicifolia*. The segmentation method was verified on this basis. The values of the metrics MAE (mean absolute error), MSE (mean square error), MAPE (mean absolute percentage error) and MPE (mean percentage error) for each plant species were calculated (Table 3, Fig. 3).

Analysis of the data obtained allows us to conclude that the segmentation algorithm works ideally with plants with a simple branched system, where all leaves grow out from the main stem, for example, *Erysimum asperum*, *Anubias congensis*, and *Campanula persicifolia*. Segmentation errors in plants with this structure only occur when segmenting young leaves whose biomass is low compared to other leaves, such as Secale Cereale.

CONCLUSIONS

This research has solved the urgent task of improving the process of scientific research in the field of micropropagation of plants for the use of intelligent modeling and 3D technologies.

The analysis showed that the existing systems of digital phenotyping examine plants without taking into account in vitro conditions, as a result of which there is no compensation for various distortions in images caused by fogging and defects in the glass of the test tube, nonlinearities at its boundaries, and glare and reflections of surrounding objects.

Methods and algorithms have been developed to solve the above problems: segmentation of plants in the image; assessing the presence of infections and diseases; building 3D models; segmentation of the obtained models into organs; and the determination of morphometric features of the test sample, which allows for a full cycle of digital plant phenotyping.

A complex of 792 units of 3D plant models of six species has been developed, built on the basis of the developed methods and algorithms. Based on the experimental data obtained, the quality metrics precision, recall, F1, MAE, MSE, MAPE, and MPE were calculated, and the adequacy of methods, models and algorithms was assessed.

The results of the study are recommended for use when creating systems for digital phenotyping of plants, including in the field of their micropropagation, intended for research laboratories of plant biotechnology, laboratories of commercial enterprises that grow planting material on an industrial scale.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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