Overview of Research on Seedling Quality Grading Based on Artificial Intelligence

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Abstract. Testing and grading the quality of seedlings is beneficial for selecting advantageous varieties. This article discusses the grading indicators of seedling quality from three aspects: morphology, physiology, and vitality. It summarizes and prospects the research status of intelligent grading methods for seedling quality at home and abroad, aiming to provide reference for exploring new and more comprehensive intelligent grading methods.

Keywords: Seedling Quality;Grading Indicators;Artificial Intelligence.

1. Quality grading indicators for seedlings

Effective seedling grading is conducive to unifying the production, design, and procurement of seedlings, achieving industrial standardization, and selecting advantageous varieties from different regions. In the early stages of seedling research, the quality of seedlings was measured by the degree to which they could achieve the predetermined seedling cultivation goals. The core definition was to use the lowest possible cost to complete the application of seedlings; With the further deepening of research, the current stage defines the quality of seedlings by assessing the degree to which they have achieved their afforestation goals based on comprehensive conditions such as the type, age, physiological status, and vitality of the seedlings[1]. By limiting a series of conditions, the definition of seedling quality is made more complete and scientific.

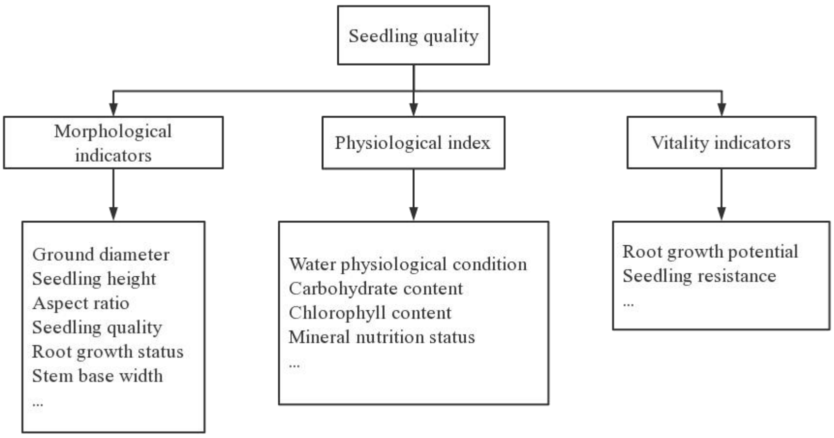

Fig.1 Quality grading indicators for seedlings

The quality and morphological indicators of seedlings mainly include ground diameter, seedling height, root system index, weight index, stem to root ratio, top bud condition, and comprehensive quality index. Affected by site conditions, the diameter to height ratio reflects the balance between seedling height and coarseness, and is a good indicator of seedling resistance and afforestation survival rate [2,3]. The stem to root ratio reflects the balance between the two parts of the seedling's root and stem. In short, due to the ease of measurement of morphological indicators, they are most widely used in the evaluation of seedling quality.

The physiological indicators of seedling quality mainly include water status, mineral nutrition status, carbohydrate content, chlorophyll content, date of breaking bud dormancy, stress induced volatile substances, etc. Usually, chemical measurement methods are used to measure physiological indicators of seedlings, which are complex, time-consuming, and require certain instruments and equipment. The practical application of physiological indicators of seedlings is subject to many limitations. The water content of seedlings largely determines their life activities, and physiological water deficiency in the root system may damage the cell wall, thereby affecting the survival rate of afforestation [4,5,6]. Mineral nutrients play a crucial role in the physiological processes of seedlings, especially nitrogen, which plays a greater role in seedling quality than phosphorus and potassium. After afforestation, seedlings with high nitrogen content in their leaves exhibit strong photosynthesis, which is beneficial for carbohydrate synthesis, thereby inducing rooting and promoting stem growth. Carbohydrates are products of photosynthesis, accounting for 75%[7] of the dry weight of seedlings. After the seedlings are raised and before afforestation, their life activities are maintained entirely by stored carbohydrates, and the health status of the seedlings can also be quantitatively reflected by measuring the chlorophyll content of their leaves.

The growth performance index of seedling vitality can best reflect the vitality status of seedlings, because the growth performance index of seedling vitality is to measure the performance status of the entire seedling under certain conditions, which integrates the morphology and physiology of the seedling [8].The Root Growth Potential (RGP) is the ability of seedlings to root in the most suitable growth environment [9,10]. It not only depends on the physiological condition of the seedlings, but also is closely related to the morphological characteristics, biological characteristics of tree species, and growth season of the seedlings, which can better predict the vitality of the seedlings and the survival rate of afforestation [11].

2. Intelligent grading of seedling quality

In the past, seedlings were mainly classified manually, but manual classification had significant drawbacks and shortcomings, such as high labor intensity and low work efficiency. At the same time, due to insufficient or negligent technical judgment of screening personnel, it may lead to varying degrees of misselection. At the same time, manual measurement can also cause errors in the measurement results, leading to inaccurate classification results and insufficient classification accuracy, affecting the design and production of subsequent seedlings.

In recent years, with the continuous development of forestry science and technology, seedling grading methods have become increasingly intelligent. Computer vision technology, hyperspectral imaging technology, and various intelligent machine learning algorithms have been widely used in seedling quality grading. Intelligent grading of seedlings refers to the use of computer image processing, data analysis, and intelligent calculation to construct a computer vision system that replaces manual grading and achieve automatic grading of seedlings. The image of the seedlings is collected into a computer through a camera, and processed and analyzed using image processing, pattern recognition, and neural network technology to identify the morphological features of the seedlings. At the same time, the morphological feature parameters of the seedlings are measured, and the quality evaluation of the seedlings is obtained through computer data processing and analysis, thereby grading the seedlings [12].

2.1 Domestic research status in CHINA

To address the key technical issues of the automatic grading system for coniferous tree seedlings based on computer vision technology, Jingfeng Bai et al.[13] proposed a new method for extracting computer vision features of seedlings using accurately located seedling image feature markers. This method analyzes the morphological characteristics of seedlings and obtains 5 feature marker points and a matrix of axial edge marker points for seedlings using the grayscale matrix of seedling image and the grayscale matrix of background separation, respectively. The experimental results show that this method has the advantages of fast calculation speed, easy implementation, and accurate measurement.

Junming Xie, Lihai Wang, Wenshu Lin, et al.[14] took Korean pine with different decay degrees as the research object, selected nondestructive, resistance loss and abnormal area ratio of heartwood and sapwood as the independent variable of the model, and the decay grade as the dependent variable, and used nondestructive testing and repeated layered K-fold cross validation methods to establish a random forest tree decay classification model. The results showed that the training and testing accuracy of the random forest decay classification model were 100% and 90% respectively, indicating that it had good fitting effect and strong generalization ability. The random forest correctly identified the decay grades (I, II, IV, V), and the recall rate was 100%. There was one case of wrong judgment of decay grade III. The accuracy rate of grading decayed standing trees was as high as 96.67%. The micro and macro average AUC values of random forest were 0.9792 and 0.9708,respectively.

Yurong Li et al.[15] utilized advanced stereo vision 3D reconstruction technology and near-infrared spectroscopy detection technology to achieve precise measurement of static indicators of Pinus massoniana seedlings. Firstly, establish a software and hardware experimental platform, obtain image sequences through an image acquisition system, and reconstruct a 3D model of Pinus massoniana seedlings using algorithms on a computer to extract morphological indicators of Pinus massoniana seedlings; Then, the chemometrics method is used to mine the useful information in the near-infrared spectrum, and the partial least squares regression method is used to establish a linear model, so as to achieve the rapid and nondestructive determination of the main physiological indicators of seedlings. Obtaining morphological and main physiological indicators of Pinus massoniana can help screen excellent afforestation seedlings.

The detection of seedling morphological indicators is easier to achieve and easier to control compared to the detection of physiological indicators. Therefore, in the actual production process or seedling grading process, the morphological indicators of seedlings are often used as grading indicators for seedling quality. Among the morphological indicators of seedlings, intuitive and easy to measure seedling height characteristics and root growth status are often selected as grading indicators based on other indicators. One important factor in the grading process is the measurement of indicators. Realizing accurate measurement of selected indicators helps to provide effective data support and information input for intelligent automatic grading of seedlings.

Lu Wei et al.[16] designed a micro root morphology real-time in-situ collection system for multi-point measurement to obtain the root growth morphology of shallow root crops in real-time. The system mainly consists of micro cameras and optical amplification elements (with a volume of 1.5cm3), and the collected images are sent to the terminal through wireless modules. Using a root image analysis method based on regional growth, starting from the corrosion image and ending from the expansion image, combined with similarity criteria for regional growth, regional labeling, and regional preservation, to filter out the interference caused by soil pores and impurities on the image, extract the root contour, and calculate morphological parameters such as root length density and average root diameter through image morphology.

Liu Kai [17] proposed a root detection technology based on micro root canal and image processing technology, which solved the key problem of root detection in complex environments in large-scale forest root zones. He proposed and adopted a morphological improved fuzzy C-means root segmentation method and an adaptive neural network root segmentation method based on growth significance, Not only has the efficiency of image processing been improved, but also the accuracy of image segmentation has been improved, achieving automated and batch processing of root images.

Liyan Yang et al. [18] designed a laser photogrammetric tree detector based on the theory of photogrammetry, tree measurement, image processing technology and sensor technology. By compiling three modular programs and using Java language on the Android Studio development platform, the measurement functions of DBH, tree height, and stand structure parameters are achieved. 21 trees were measured for diameter at breast height, tree height, and 15 central trees in a sample plot were tested for forest spatial structure parameters. The average absolute value of relative error in diameter at breast height measurement was 2.55%, the average absolute value of relative error in tree height measurement was 2.82%, and the average absolute value of relative error in angular scale and size ratio measurement was 2.50% and 2.86%, respectively, The results of mixed degree measurement are the same as those of traditional measurement methods, and can meet the accuracy requirements of forestry surveys.

2.2 Current research status abroad

Accurately and quickly grading seedlings to ensure their pre planting quality has become a crucial issue. However, manually measuring morphological indicators to classify seedlings is labor-intensive and inaccurate, so it is highly desirable to be replaced by machine vision.

McGuinness Benjamin et al.[19] proposed three algorithms that utilize machine vision systems combined with denoising and segmentation image processing techniques to measure the root crown diameter, seedling height, and root distribution characteristics of seedlings. When segmentation is based on pixel variance, unnecessary information is removed through dilation and corrosion. The processing time for the entire seedling is approximately 30 milliseconds. Provide effective and accurate data for the input of seedling quality automatic classifier.

Suo Rui et al. [20] proposed an apple seedling segmentation method based on BlendMask and ResNet-101 for transfer learning. The Azure Kinect DK sensor captured a total of 450 original images. A new labeling strategy was adopted to label the roots, rootstocks, grafting bodies, and scions of apple seedlings. The average accuracy rates of the roots, rootstocks, grafting bodies, and scions were 98.9%, 89.3%, 90.6%,and 85.6%. The labeling strategy is beneficial for improving the segmentation accuracy of slender objects, effectively segmenting seedlings, and facilitating machine vision measurement of morphological indicators and levels.

Wang P et al. [21] designed and implemented a low-cost automated ground laser scanner based on the SICK LMS-511 two-dimensional laser scanning sensor and stepper motor, which can perform three-dimensional scanning of forest trees. Based on point cloud data, trees are detected through a single slice of a single scan in the graph, and local ground planes are fitted for each detected tree. Then, specific software were used to automatically estimate the breast height, tree height, and diameter of tree position. The experimental results indicate that the BEE scanner can efficiently estimate the structural parameters of artificial forest trees.

Hyyppa J et al. [22] calculated tree height using digital terrain and canopy models obtained from laser scanner data. By using image vision methods such as segmentation to analyze the 3D tree height model, using high pulse rate laser scanners to provide data, locate a single tree, estimate its height, crown area, and use this data to obtain stem diameter, stem number, base area, and stem volume. The advantage of this method is that it can directly measure physical dimensions from trees and use this information to calculate the required forest properties.

Zarco Tejada P J et al. [23] used passive sensors to evaluate canopy biophysical parameters and quantified the height of trees in discontinuous tree crowns using low-cost cameras on unmanned aerial vehicles (UAVs). Using GPS in real-time kinematics (RTK) mode, the height of 152 trees in two different study areas was measured in the field. The validation evaluation results of VHR DSMs for estimating tree height showed R-2=0.83, with a total root mean square error (RMSE) of 35 cm, and a relative root mean square error (R-RMSE) of 4.38% for trees with heights ranging from 11.5 to 1.16 m. Research using this drone system and photo reconstruction method in two orchards emphasizes that a low-cost method based on onboard consumer grade cameras, manually launched drone platforms, can provide accuracy comparable to the expensive and more complex Light Detection and Ranging (LIDAR) systems currently used in agricultural and environmental applications.

Celestino Ordóez a et al. [24] proposed a method for automatically identifying tree trunks and estimating tree height and diameter based on land laser scanning (TLS) data. This method is based on stem isolation and vertical continuity. Firstly, create a highly normalized version of the point cloud. Therefore, the stem is personalized, and an iterative process is performed on points with chest height to estimate the diameter, and the tree height is calculated after denoising and clustering the points of each tree. This method was tested at three different locations. All elements detected as trees are actual trees, and over 99% of the trees in the plot are detected. The root mean square error (RMSE) of the estimated diameter at breast height (DBH) of the experimental plot is 0.8-1.3 cm, and the total height (TH) of the tree height RMSE ranges from 0.3 to 0.7 m. In the studied case, the algorithm demonstrated robustness to the presence of steep or irregular terrain, low vegetation and artifacts at chest height, blurred use of single or multiple scans, and tree density in the image.

The quality grading of seedlings is usually carried out by grading and screening a certain number of seedlings in a relatively wide range of artificial or natural forests. Due to the large number of seedlings, the field workload for achieving seedling grading is significant. To address this issue, some researchers have shifted their research direction to the field of unmanned aerial vehicle (UAV) LiDAR, which plays a significant role in reducing field workload and increasing the speed of collecting classified input feature information.

Corte A et al. [25] used an unmanned aerial vehicle LiDAR system (GatorEye) to automatically measure the diameter at breast height and total height of individual trees. In high-density unmanned aerial vehicle LiDAR point clouds, algorithms are applied for individual tree detection and direct measurement of tree height and diameter at breast height. The correlation coefficients (r) between the field observation values and the measured values derived from drone LiDAR for diameter at breast height and tree height are 0.77 and 0.91, respectively.

3. Summary and Outlook

With the continuous improvement and development of science and technology, intelligent grading technology for seedlings has achieved a series of achievements, but it can also be seen that there are still many shortcomings:

1) Due to the limited research cost, only targeted research and analysis of certain performance can be conducted during the research process, which leads to a small number of detection indicators for evaluation and a single research method that cannot comprehensively and accurately analyze and evaluate the quality of seedling plots.

2) Different seedlings have different quality grading methods and exhibit different plant traits, with multiple indicators and complex factors to consider. Systematic management analysis has not yet been formed, which is not conducive to data query and method improvement in subsequent research.

3) The intelligent grading of seedlings emphasizes the use of mechanical intelligence methods to replace manual labor, leading to a significant increase in the cost of various equipment and technologies. The forestry work environment is very complex, and the accuracy and speed of machine recognition images are not enough.

Based on the above issues, prospects for the development of intelligent grading of seedling quality in the future are proposed:

1) Integrating previous research data and research directions to form an intelligent grading system for seedlings, forming a more comprehensive information system, will help future research become more targeted.

2) Improve the image algorithm for detecting seedling quality evaluation indicators, collect image information collected by machine equipment, and automatically generate three-dimensional and intuitive image data to improve detection accuracy.

3) To meet the demand for rapid collection of plant phenotype information, high-precision and non-destructive methods should be further utilized to improve plant function and structure research, and intelligent information technology research and development such as digitization of forest germplasm information and high-throughput phenotype monitoring of trees should be carried out. Combining artificial intelligence algorithms to deeply mine excellent genetic resources in forest trees [26].

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