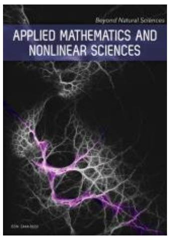
sciendo Applied Mathematics and Nonlinear Sciences, 9(1) (2024) 1-13



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Application of digital design technology in the design of intelligent agricultural machinery and equipment

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Submission Info

Communicated by Z. Sabir
Received May 4, 2022
Accepted October 26, 2022
Available online May 5, 2023

Abstract

Today, China has become the world's largest agricultural machinery and equipment countries and the use of countries, agricultural machinery industry for more than a decade to maintain high growth, along with three revolutionary changes in agricultural technology, has initially ushered in the development of artificial intelligence stage. At present, relative to the weak foundation of China's agricultural machinery standardization work and the requirements of high integration of technology and multidisciplinary integration of artificial intelligence, there are bottlenecks that constrain the problem. This paper makes a directional discussion on the direction of standardization breakthrough through the analysis of digital design technology and typical applications at home and abroad, the analysis of standard transformation of scientific and technological achievements, and the analysis of current problems. Aiming at technical standards development, implementation, and improvement to promote technological innovation, application, and improvement of intelligent manufacturing of agricultural machinery products. So that scientific and technological innovation continues to enhance the level of technical standards, technical standards continue to promote the transformation of scientific and technological achievements. Technical standards and intelligent agricultural machinery lend each other in international competition and become a strategic means to participate in international cooperation and competition. Accelerate the transformation of the old and new dynamics of the agricultural mechanization industry, and realize the standardization and internationalization of the intelligent agricultural mechanization industry.

Keywords: Agricultural machinery and equipment; Artificial intelligence; Multidisciplinary integration; Digital design technology; Intelligent agricultural machinery
AMS 2020 codes: 91F99

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ISSN 2444-8656
https://doi.org/10.2478/amns.2023.1.00215

1 Introduction

China's agricultural science and technology development mode by three revolutionary changes from traditional to modern gradually, agricultural machinery and equipment along with the development of agricultural modernization is gradually entering the era of intelligence. As a leading technological progress of agricultural machinery standardization is still lagging behind the phenomenon and the weak link of the lack of standards [1-3]. In the context of intelligent agricultural machinery calling for a new standardization system, the development process of agricultural mechanization to supplement and change the shortcomings of the standardization of agricultural machinery construction. In the long run, the development of intelligent agricultural machinery is a global beacon. In recent years, intelligent agricultural machinery has been developing rapidly in China [4]. Focusing on optimizing industrial upgrading, promoting agricultural development, accelerating the development of the "beautiful countryside" project, and combining the development of intelligent agricultural machinery and its own characteristics of poverty alleviation, we help to combat poverty in a targeted manner. As early as November 2013, General Secretary Xi Jinping first made the important instruction of "seeking truth from facts, adapting to local conditions, classifying and guiding, and precisely alleviating poverty" during his inspection in Xiangxi, Hunan Province. In January 2014, the General Office of the Central Committee of the Communist Party of China officially issued a document to promote the full implementation of the "precise poverty alleviation" instruction [5]. With the revolutionary change of design tools, data became the main design vehicle, starting from the digital power industry in the last century, the upgrading of production methods and the emergence of modern management technologies together shaped a new face of the industry, and the resulting worldwide concept of data-driven digital design gradually took root and started to move from concept to practice [6, 7]. Data, as the object of design has become the most basic element, is re-architecting the connection of all knowledge workers from a higher dimension. An ecology of digital design is taking root and will grow into a lush digital forest in the future.

At present, foreign companies Southern Cross and Reinke have produced intelligent remote-controlled sprinkler units. In computer-controlled precision sprinkler technology, soil moisture information can be measured using moisture sensors buried in the ground, and there are intelligent systems that can determine the irrigation schedule and irrigation volume for crops by detecting changes in the diameter of plant stems and fruits [8, 9]. In addition, computer-based irrigation monitoring and management is also an important element of intelligent precision sprinkler technology. All U.S. irrigation districts have established automatic monitoring and control systems to varying degrees. It uses electronic instruments to control water level, gate position and opening degree and other information, which is transmitted to a computer terminal through a microwave relay station, calculates the flow rate of each gate, converts the data automatically into analog signals, and then interprets them through a computer to manipulate the opening and closing of gates and pumps according to water demand requirements and to display their operation and results [10]. In Japan, grafting robots, cutting robots, transplanting robots and harvesting robots have been developed as early as the late century [11, 12]. Danish scientists have developed a robot that can be used to weed agricultural fields, which not only reduces farmers' hard work but also reduces the environmental pollution caused by herbicides. Spain invented a citrus picking robot, the UK's Cilso Institute developed a mushroom picking robot, France developed a sorting robot, and the US invented a multipurpose automated combine harvesting robot, among others [13-16]. Agricultural robots that have been developed in China include plowing robots, weeding robots, fertilizer robots, spraying robots, vegetable grafting robots, harvesting robots, and picking robots [17-19]. Vegetable grafting robots have been successfully developed in China, and experimental grafting production has been successfully carried out. The vegetable robot developed by China Agricultural University solves the problems of tenderness, fragility and inconsistent growth of vegetable seedlings, and can be widely used for grafting vegetable seedlings such as cucumber, watermelon and melon [20]. China has also successfully developed a tomato-picking robot with a color camera that can determine the ripeness of the fruit.

As China enters a new development stage, accelerating the construction of a strong manufacturing country and vigorously developing advanced manufacturing industries have become important strategies for high-quality socioeconomic development in China [21]. In the face of an increasingly competitive market environment, China's machinery manufacturing should take intelligent manufacturing as the main direction to promote industrial technology change and upgrade, and to promote fundamental changes in the manufacturing industry model and enterprise form. Based on the development of big data, cloud computing and robotics, it is important to integrate modern digital design and manufacturing technologies into the field of machinery manufacturing [22-24]. Therefore, in order to promote the high-quality development of intelligent machinery manufacturing, China should take advantage of modern digital design and manufacturing technology to create personalized, flexible, and low-energy mechanical equipment products [25]. Modern digital design and manufacturing technology mainly integrates Internet, cloud computing, blockchain and robotics with mechanical design and manufacturing technology to simulate and model mechanical products according to customer needs and work characteristics, thereby producing mechanical products that meet user needs. The key technology of intelligent manufacturing is digital design and manufacturing. To this end, a digital design system for agricultural machinery has been implemented based on big data prediction model technology, which is capable of automating the design of agricultural machinery parts.

This paper combines the characteristics of digital design of agricultural machinery and the advantages and disadvantages of several big data mining techniques, and chooses to use BP neural network model to optimize the agricultural digital design process. The BP neural network model is an artificial neural network algorithm that simulates a set of information processing systems that can achieve certain special functions based on the understanding of the human brain, and consists of a large number of neuron nodes interconnected to form a complex network. Compared with the traditional mechanical design and manufacturing technology, modern digital design and manufacturing technology highlights the advantages of "digital". With the development of information technology, artificial intelligence has gradually become the mainstay of science and technology. The use of artificial intelligence and computer-aided software to realize the digital design of agricultural machinery is of great significance to improve the manufacturing capacity of agricultural machinery products, shorten the design cycle, reduce design costs and improve the competitiveness of enterprises.

2 Methodology and construction of the model

2.1 Concept of machine digitization

Modern digital design and manufacturing technology contains a relatively rich content. Specifically include: computer technology. Computer design technology is mainly the use of computer technology to design mechanical products, such as computer-aided design (CAD) for the conception of mechanical products, functional design and other optimization, the realization of paperless operation of mechanical design, virtual design and manufacturing. Virtual technology is the most widely used technology in mechanical design and manufacturing, which mainly provides a test operation platform for mechanical product design and production by building a virtual simulation environment, so as to achieve the purpose of networked parameter optimization and adjustment. Off-site collaborative design. Off-site collaborative design mainly starts from the process and collaboration management to realize the intensive and comprehensive management of mechanical design and manufacturing.

Concept and industrial design. Conceptual design is designed around the needs of the customer, which is mainly the integration of design concepts into the entire process of designing and producing mechanical products. Industrial design is the design of the layout, form and interpersonal engineering of machinery, so as to make the product and the user have a good affinity and match. Of course, in addition to the above technologies, digital design and manufacturing technologies also include robotics, neural network technology, etc. Combined with years of practical investigation, the application of modern digital design and manufacturing technology in mechanical design and manufacturing is reflected in the following aspects. Virtual reality technology is an important part of modern digital design and manufacturing technology, and its application in mechanical design and manufacturing is the most common, the main role is to build a virtual simulation environment to provide a virtual experimental platform for mechanical design and manufacturing, so as to achieve the most optimal design. Based on the development of intelligent manufacturing, the main trend of modern intelligent manufacturing is to realize the integration of mechanical design and manufacturing. Collaboration technology can make products share information in design, let all workers of products participate in design, help designers develop ideas, and make products more adaptable to practical applications, can process and analyze information according to different design tasks and design problems, make design work more efficient, improve the design and manufacturing level of agricultural machinery, and save design and manufacturing costs for enterprises.

Intelligent agricultural equipment refers to the modern communication technology, software and hardware integration technology, remote sensing control technology, big data cloud platform technology and the integration of agricultural machinery and agronomy technology in the traditional agricultural machinery focus on the embodiment. It is generally professional, stable and reliable, labor-saving and efficient, intelligent and accurate, etc. Through flexible and efficient operating system, system-on-chip (SoC), wireless mobile transmission technology and various interactive sensors with the application, to achieve the purpose of accurate acquisition of various operational data, and then deep mining, as shown in Figure 1.

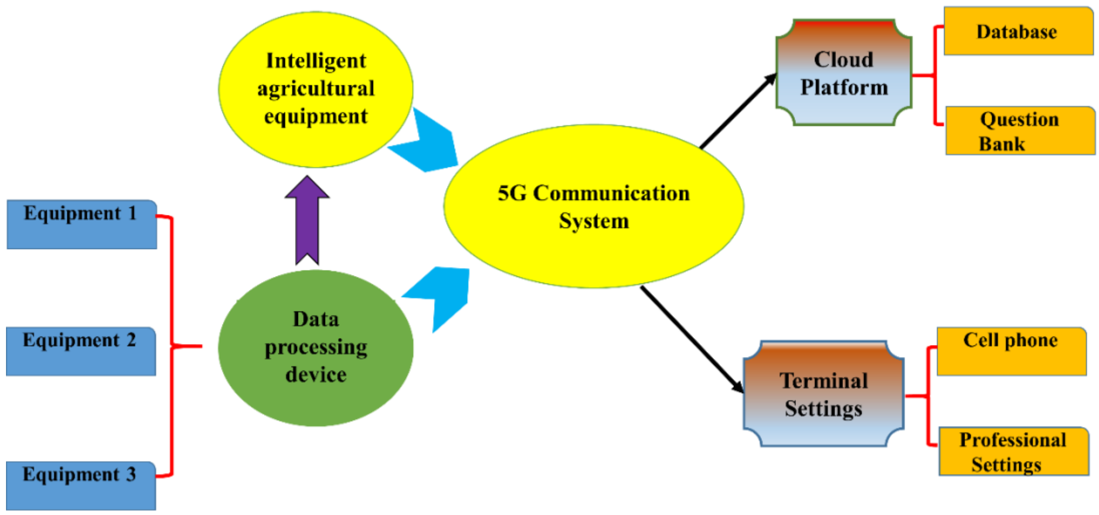

Figure 1. Composition structure diagram of intelligent agricultural machinery and equipment

2.2 Construction of digital model of machinery

The basic principle utilized in the numerical model is phase conjugation. The field measured by the wavefront sensor is a variable field with phase errors and can be expressed as:

$$E_1 = |E| e^{f\phi} \tag{1}$$

Where E and E_1 represent the modulus of the variable field and $e^{f\phi}$ is the propagation index per unit optical frequency. And the variable fields obtained by conjugate modulation of the adaptive optics system are

$$E_1 = |E| e^{-t\phi} \tag{2}$$

There are four main methods for wavefront simulation of optical systems: the Zernike polynomial K-L function expansion method, the Fourier method, the wavelet method, and the ARIMA method. Among them, the Zernike method is suitable for wavefront simulation in circular domain, and the wavelet method is computationally intensive and cannot meet the real-time requirements. The Fourier method has great shortcomings in the long-time simulation process. Therefore, the Zernike method is now the most widely used method for adaptive optical systems. Usually, the beam wavefront propagates according to the basic formula of Gaussian beam. The beam has different propagation formulas according to different distribution methods as follows:

For the propagation of light sources in the conventional sense, the expression for the transverse light intensity distribution is:

$$I(Z,\Upsilon) = \frac{2P}{\pi\omega(\mathrm{Z})^2} \exp(\frac{-2\Upsilon^2}{\omega(\mathrm{Z})^2}) \tag{3}$$

I is the distance per unit of light traveled and represents the distance that light travels in a vacuum in one year. In addition, the expression for the radius of the $1/e^2$ beam is:

$$\omega(\mathrm{Z}) = \omega_0 \sqrt{1+\left(\frac{\lambda \mathrm{Z}}{\pi\omega_0^2}\right)^2} \tag{4}$$

Z is the magnitude of the beam radius and ω_0 is the radius of curvature. For the wavefront radius of curvature, the corresponding equation is:

$$R(\mathrm{Z}) = \mathrm{Z}\left[1+\left(\frac{\pi\omega_0^2}{\lambda \mathrm{Z}}\right)^2\right] \tag{5}$$

Similarly, Z is the magnitude of the beam radius and ω_0 is the radius of curvature. The consensus expression for the far-field divergence angle is:

$$\theta = \frac{\lambda}{\pi\omega_0} \tag{6}$$

Where λ is the unit wavelength and ω_0 is the radius of curvature. In addition, the Rayleigh distance has the corresponding expression:

$$Z_R = \frac{\pi\omega_0^2}{\lambda} \tag{7}$$

Assuming that the Gaussian beam encounters a circular aperture during propagation, the power ratio of the beam passing through the circular aperture is:

$$1-\exp(\frac{-2a^2}{\omega^2}) = \frac{1}{e^2} \tag{8}$$

a is the radius of the circular aperture and 1/e² is the radius of the beam, i.e., the beam diameter at which the light intensity drops to 1/e² of the central light intensity. In addition, since the beam has transverse propagation, the transverse light intensity distribution of the Gaussian beam is:

$$I(r) = I_0 \exp(\frac{-2r^2}{\omega^2}) = \frac{1}{e^2} \tag{9}$$

Where r is the distance between a point in the beam and the central axis and 1/e² is the radius of the beam. Ultimately, by integrating over the entire circular aperture, we can calculate the power ratio of the Gaussian beam through the circular aperture as:

$$\frac{P(a)}{P} = \int_0^a I(r)\frac{2\pi r dr}{P} = 1-\exp(\frac{-2a^2}{\omega^2}) \tag{10}$$

Where P is the total power of the beam and P(a) is the power transmitted from the circular aperture. According to the above formula, then the transmittance is 1-1/e², which is 86.5%. If the radius of the aperture is 0.5, then the transmittance is 39%; if the radius of the aperture reaches 2, then the transmittance is close to 100%.

Based on the above analysis, attention must be paid to the through-aperture of the optical element in laser applications. For an ideal Gaussian beam, assuming a loss of less than 1% is required, the through-aperture of the optical element should be greater than 1.5 times the 1/e² radius of the incident beam or greater than 2.6 times the radius. The conversion relationships between the different radius standards for Gaussian beams are described below. For consistency, the above uses r (x%) to denote the radius containing x% of the total beam power, and these conversion relationships are easily derived from the equations in the previous section. r (86.5%) is often referred to as the 1/e² beam radius, and the beam power within this radius is 1-1/e², or 86.5%, while r (50%) is also called the 3 dB radius.

Assuming that the Gaussian beam propagates through an ideal thin lens, we can calculate the parameters of the transmitted beam according to the following equation:

$$\frac{1}{\omega_{0\mathrm{out}}^2} = \frac{1}{\omega_{0in}^2}\left(1-\frac{d_{in}}{f}\right)^2 + \frac{1}{f^2}\left(\frac{\pi\omega_{0in}}{\lambda}\right)^2 \tag{11}$$

$$d_{out} = f + \frac{f^2(d_{in} - f)}{(d_{in} - f)^2 + \left(\frac{\pi\omega_{0in}}{\lambda}\right)^2} \tag{12}$$

Where d_{in} and d_{out} are the incoming and outgoing unit transmission distances, f is the frequency of the light, and ω_{0in} is the rotational inertia within the light. Because the output of a single-mode fiber is close to a Gaussian beam, the essence of single-mode fiber collimation is the special case of a Gaussian beam propagating through a lens, when the following equation is satisfied as a boundary.

$$d_{in} = f \tag{13}$$

$$\omega_{0in} = \frac{MFD}{2} \tag{14}$$

$$\omega_{0out} = \frac{D}{2} \tag{15}$$

MFD is the fiber mode field diameter, D is the collimated output beam diameter, ω_{0out} is the full divergence angle of the collimated output beam, simplifying the above equation to obtain the main parameters of single-mode fiber collimation:

$$D = \frac{4f\lambda}{\pi MFD} \tag{16}$$

$$d_{out} = f \tag{17}$$

$$\Theta = \frac{MFD}{f} \tag{18}$$

Where MFD is the fiber mode field diameter, d_{out} is the direct outgoing unit transmission distance, f is the frequency of the light, and D Θ is the modulus of the light. After the final output through the collimating lens, the extent to which the beam can be kept collimated is the lens focal length f plus the Rayleigh distance of the output beam:

$$f + Z_R = d_{out} + \frac{\pi\omega_0^2}{\lambda} \tag{19}$$

The unfolded expression is:

$$f + Z_R = \frac{f^2(d_{in} - f)}{(d_{in} - f)^2 + \left(\frac{\pi\omega_{0in}}{\lambda}\right)^2} + \frac{\pi\omega_0^2}{\lambda} \tag{20}$$

Where d_{in} and d_{out} are unit transmission distances, f is the frequency of the light, and ω_{0in} is the rotational inertia within the light. Z_R is the unit polarization of the output of the lens.

Combining the digital modeling approach introduced above and the features of the heuristic collaborative filtering algorithm, the calculation formula is improved to avoid finding the nearest neighbor items in the whole space. The above algorithm for data acquisition allows the analysis of the use of resources and the trajectory of the sample movement. Sampling can be done for a certain area for agricultural equipment at work to make it more in line with the actual needs, to achieve closed-loop feedback, and to improve the patterned collection of data at high quality and high speed.

3 Evaluation of models for digital inspection data sets of machinery

The digitized dataset has its own characteristics unlike the traditional dataset, and its large bias between data leads to poor generalization of the digitized dataset: (1) Large variation in scale between targets, e.g., airports and ships in targets, and targets in the same category can differ due to differences in detector performance and environment. (2) The existence of dense small targets, which greatly increases the difficulty of target detection. (3) The uncertainty of the targets, unlike the traditional dataset, the view of the digitized dataset is overhead and the targets have arbitrary orientation. Considering the difficulties of digital dataset detection, selecting a high-quality dataset is necessary to improve the correctness of the target detection model. For this purpose, we collected data on the different distribution of the tail flow of the equipment and the different depths of the operation. In addition, the collected data are generalized and analyzed to derive the trajectory of the equipment and the working status of the equipment.

In this regard, a test area with an area of 256m×525m was selected, without considering the viscous effect of the machinery itself. In order to study the characteristics of the submarine wake, the effects of Fn (wake oscillability), depth and speed variations of different influencing parameters on the mechanical wake were considered, respectively. Ensuring that other parameters are the same, three data with Fn of 0.18, 0.30 and 0.45 are selected in this section to model and simulate the mechanical wake respectively. The mechanical wake is a criterion to evaluate whether the mechanical equipment is operating properly or not. Here, we specifically transform the collected simulation data into micro variables and then perform digital model simulation to finally visualize and read the simulation data. Figure 2 shows the radial distribution of the mechanical wake at different data acquisition angles. It is obvious that the wave amplitude at the wake axis increases with the increasing data acquisition range, and at the highest point it exceeds 37 m. The wavelength of the wake at the axis also increases. For the radial distribution of the mechanical design wake, the wave amplitude of the wake is decreasing with the increase of the radial distance, and after keeping the basic stability, there are small fluctuations.

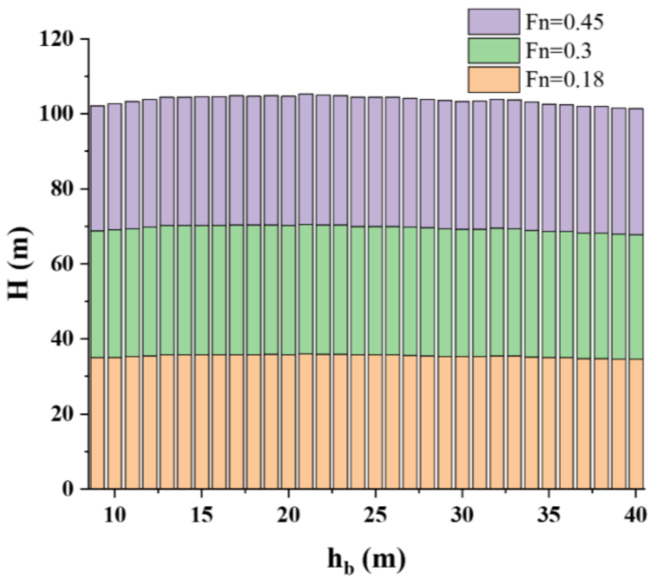

Figure 2. Radial distribution of the mechanical design wake at different data acquisition angles

Figure 3 shows the axial distribution of the wake at different data acquisition angles. It is easy to see that the wave amplitude of the wake at the axis of the wake is increasing with the increasing data acquisition range, and the wavelength of the wake at the axis is also increasing at the highest point over 65m. For the radial distribution of the mechanically designed wake, the wave amplitude of the wake is increasing with the radial distance, and the fluctuation decreases after keeping the basic stability.

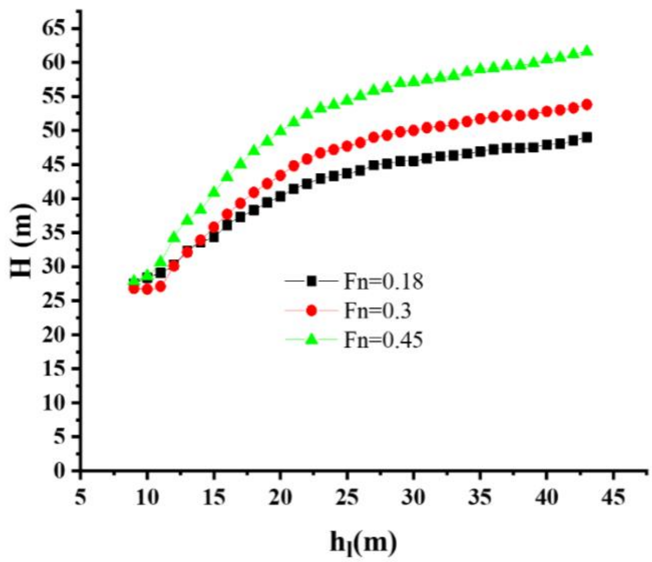

Figure 3. Axial distribution of the mechanical design wake under different data acquisition angles

The navigation depth directly affects the development of the mechanical wake, and to ensure that other parameters are the same, three kinds of data are selected for the navigation depth of 10m, 20m and 30m, respectively, and the mechanical wake is modeled and simulated. As shown in Figure 3, in general, the fluctuation of the mechanical wake is rapidly decreasing with the increasing navigation depth, and the fluctuation has decreased by an order of magnitude by the time the navigation depth reaches 32m, while the navigation depth has less influence on the shape of the mechanical wake. In terms of details, the transverse wave propagates mainly along the *x*-direction and the divergent wave propagates mainly along the *y*-direction, and the characteristics of the transverse wave and the divergent wave remain basically the same as the navigation depth keeps increasing.

Figure 4 shows the axial distribution of the mechanical wake and the radial distribution of the mechanical wake. In Figure 4, with the increasing depth of navigation, the wave amplitude at the axis of the wake is increasing, and at the depth of 31m, the wave amplitude at the highest point of the mechanical design wake has dropped to 52m, and the wavelength of the wake at the axis is basically unchanged. For the radial distribution of the mechanical design wake, the wave amplitude of the wake is increasing with the radial distance, and after keeping the basic stability, there are small fluctuations.

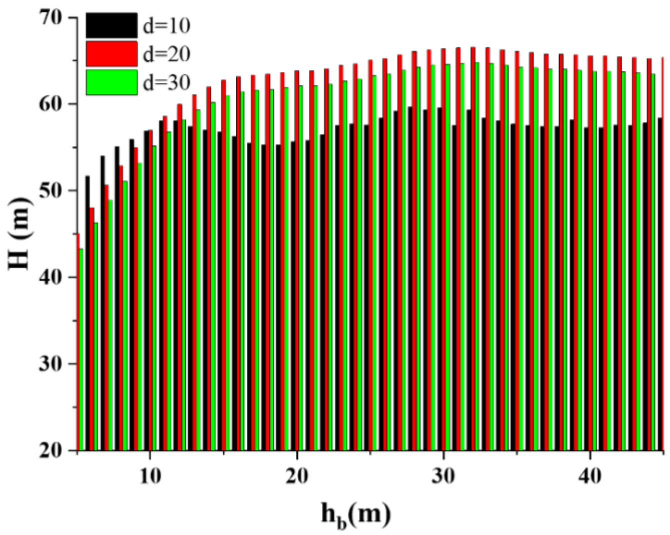

Figure 4. Radial distribution of mechanical design wake at different depths

As shown in Figure 5, with the increasing depth of navigation, the wave amplitude at the axis of the wake decreases continuously, and at the depth of 30m, the wave amplitude at the highest point of the mechanical wake has decreased to 36m, and the wavelength of the wake at the axis is basically unchanged. For the radial distribution of the mechanical wake, the wave amplitude of the wake is all decreasing with the increase of the radial distance, and after keeping the basic stability, the small fluctuations no longer appear.

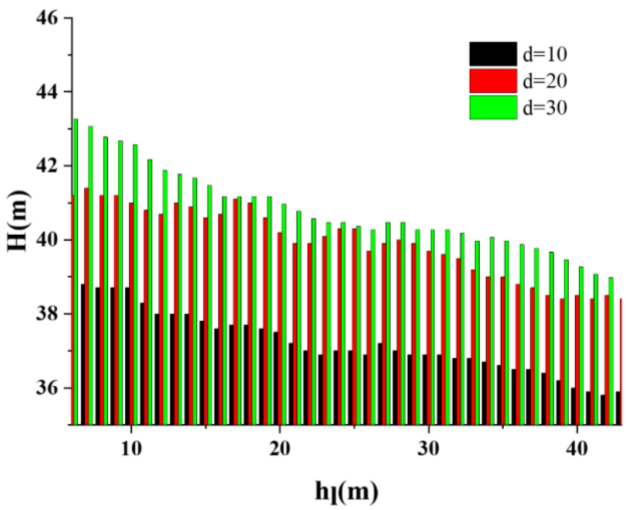

Figure 5. Axial distribution of mechanical design wake at different depths

The mechanical design sailing speed also directly affects the development of the mechanical wake, to ensure that other parameters are the same, three kinds of data with speeds of 5m/s, 10m/s and 15m/s are selected to model the mechanical design wake respectively. In general, the fluctuation of the mechanical wake is increasing as the sailing speed increases, and the mechanical wake is more dense at the same distance. In terms of details, the transverse wave propagates mainly along the x-direction and the divergent wave propagates mainly along the y-direction, and the characteristics of the divergent wave become more obvious as the navigation speed keeps increasing, while the shape of the mechanical wake shows a strong transverse wave characteristic at the speed of 5m/s.

After simulating the different influencing factors of mechanical wake flow separately, the data of the data are unified in this section as shown in Table 1.

Table 1. Influence of different factors on mechanical design wake

	Fn (0.18)	Fn (0.3)	Fn (0.45)	V (1)	V (5)	V (10)	V (15)
H_{max}	2.3	2.1	2.9	5.9	3.9	3.9	5.7
H_f	2.7	1.7	1.7	6.2	6.3	7.9	4.9
H_b	3.7	1.6	3.9	3,9	5.7	6.2	4.7
H_l	3.2	2.6	4.3	7.9	7.3	6.8	3.7
H_d	2.4	3.8	4.9	8.0	9.1	8.2	4.6

During the training process of the model, the change of the loss curve is relatively stable. In Table 1, the values of the loss function H decrease continuously with the increase of the number of Fn, and finally stabilize. It can also be seen that there are fluctuations in the drop rate of the loss curve during the descent, which is caused by the cosine annealing learning rate changing during the training process. As the improvements continue to increase, the value of the loss function after stabilization decreases. Although the trend of the final loss value does not directly reflect the effectiveness of the model, it indicates that the model has been adequately trained.

Table 2. AP values under different improvement measures

Basic model	RNMS	K-means	AP_{ship}	AP_{har}	AP_{scar}	AP_{bcar}	mAP
83.4	92.1	93.1	92.4	93.9	93.3	93.9	85.7
74.9	92.6	94.7	91.9	93.2	86.4	87.9	94.9
83.9	93.3	95.6	93.6	94.9	85.9	86.2	84.7
75.8	93.9	89.6	94.5	87.9	87.5	86.8	93.7
87.2	92.9	87.8	94.3	88.0	89.9	88.2	94.6

Table 2 shows the average AP and the specific AP for each category in the case of each improvement measure. rNMS is widely used for post-processing of detection bounding boxes. By modifying the initial IOU algorithm, RNMS is more sensitive to angle changes and achieves an average precision (mAP) of 93.02%, an improvement of 2.13% over the base model. By introducing the BP neural algorithm, the size of the prediction frame is closer to the real value and the correct rate is increased to 83.14%.

The above shows that this model has good analytical prediction and excellent sensitivity determination function for the object target. Compared with ordinary models, digitized images contain many irrelevant environmental information, which is detrimental to the learning of model features and will reduce its accuracy. Therefore, in the subsequent work, we have to perform saliency enhancement on the feature degree of the dataset before training the model, and share the label information between the obtained saliency images and the original images to enhance the model's generalization application and generalization function.

4 Conclusion

This paper analyzed the current situation of the agricultural machinery industry, analyzed the reasons for the lack of digital design level in the agricultural equipment industry, analyzed the problems in the construction of digital design platform in the agricultural equipment manufacturing industry, and put forward countermeasures to promote the sharing of digital results and resources and the rapid improvement of digital design capability. Finally, from the agricultural equipment industry to enhance the level of digital design in and design software selection, the agricultural machinery industry product technology standardization, serialization and generalization to promote, the enterprise's product development of the whole process of data integration and functional integration and the application of technology to comprehensively enhance the innovation capacity of enterprises and other aspects, put forward the corresponding policy recommendations. Through the development and application of the digital system of agricultural equipment, on the basis of improving the functions of the digital design system, to further promote the depth and breadth of the application of digital design of agricultural equipment. In the computer to establish a full digital information model of agricultural equipment, so that each stage, each professional design operations can be carried out in the same database, so that the institute's product information model and the factory's information model are compatible with each other, so as to achieve the full integration of the information of each professional, each stage, each factory, to achieve parallel design operations, so that users of agricultural machinery, designers, manufacturers and environmental engineers involved in the agricultural equipment R & D design, preliminary design, detailed design and production design of the entire process. Through mutual coordination, all factors affecting resource utilization and environmental pollution in the whole life cycle of agricultural equipment from R&D and design to end-of-life dismantling are considered comprehensively to optimize each design link, reduce the reciprocal process of product production, improve the resource utilization rate of the whole manufacturing system, reduce the scrap rate and save resources.

Acknowledgements

The key scientific and technological project of Henan Province, 202102110272, Horizontal project of Kaifeng R & D innovative technology team for new agricultural machinery equipment.

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