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REVIEW ARTICLE

Application progress of machine vision technology in the field of modern agricultural equipment

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ABSTRACT

With the rapid progress of image processing algorithms and computer equipment, the development of machine vision technology in the field of modern agricultural equipment is on the ascendant, and major application results have been obtained in many production links to improve the efficiency and automation of agricultural production. In the face of China, the world's largest agricultural market, agricultural machine vision equipment undoubtedly has tremendous development potential and market prospects. This paper introduces the research and application of machine vision technology in agricultural equipment in the fields of agricultural product sorting, production automation, pest control, picking machinery, navigation, and positioning, analyzes and summarizes the current problems, and looks forward to the future development trend.

Keywords: machine vision; agricultural equipment; application; image processing; navigation

1. Introduction

Machine vision refers to the use of machines to observe and judge human vision and is a branch of artificial intelligence. Machine Vision Technology by American Scholar Roberts proposed in the mid-1960s that after half a century of development, machine vision technology has been widely used in various fields of the national economy, such as industry, agriculture, medicine, and aerospace, and has gained tremendous social and economic benefits. China is a big agricultural country, feeding 22% of the world's population with 7% of its land, and has a complete range of industries such as planting, animal husbandry, forestry, fishery, and sideline trades. Agriculture is the foundation of people's production, and agricultural machinery and equipment are important material foundations for the development of modern agriculture. In 2015, the main business income of agricultural machinery industrial enterprises above the designated size in the country reached 452.3 billion yuan, and China has become a major producer of agricultural machinery[1]. Today, with the rapid development of intelligent agriculture, agricultural equipment that integrates machine vision technology is widely used in agricultural production processes, especially in dangerous environments that are not suitable for human operation and where it is difficult for the human eye to distinguish.

Machine vision equipment can greatly improve detection accuracy and speed, improve production efficiency while avoiding the deviations and errors caused by human eye vision inspection, improve product quality, reduce labor costs, and reduce water and fertilizer loss, in line with the requirements of sustainable

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development in precision agriculture[2]. With the strengthening of research and development of agricultural science and technology and the development of the intelligent situation of agricultural equipment[3], the market potential of machine vision technology in the field of agricultural equipment will certainly be further developed and become a new bright spot of "China's intelligent manufacturing".

2. Overview of machine vision technology

Machine vision technology refers to the use of computer simulation of human vision to identify external images and provide information for analysis and judgment. A brief diagram of the machine's visual system is shown in **Figure 1**.

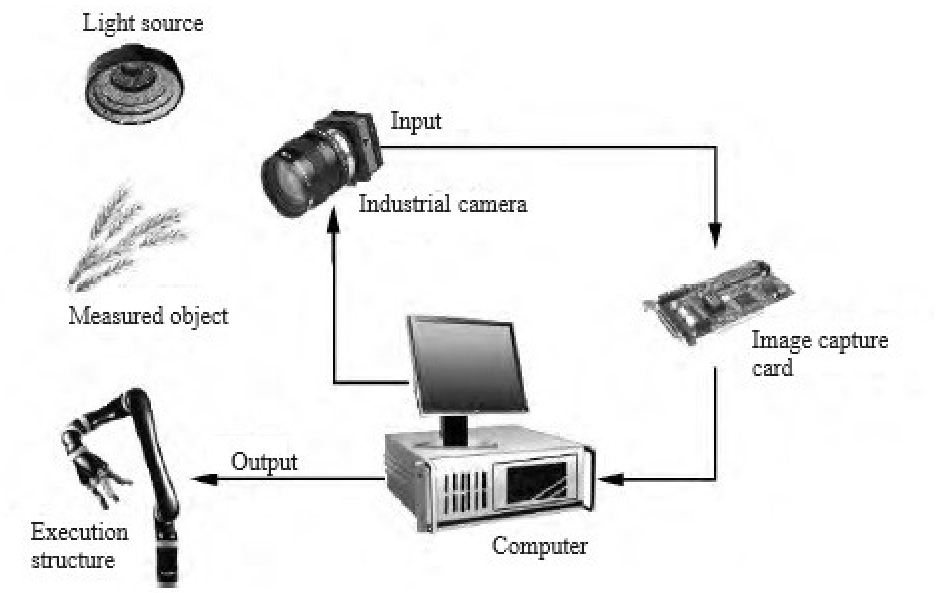

Figure 1. Machine vision system sketch.

In a typical machine vision product, the camera (CMOS and CCD, two types of sensors) collects the image of the object, and the image acquisition card converts the pixel distribution, color, and other information of the target into a digital signal and transmits it to the computer. The discriminating result is then given after processing by the machine vision software, and the actuator on the control site performs the corresponding operation. Machine vision technology is a multi-disciplinary integrated technology involving optics, mathematics, electronic engineering, computer science, and many other disciplines. The complete machine vision application system includes a light source system, an image capture model, an image digitization module, a digital image processing module, an intelligent judgment decision module, and a mechanical control execution module.

3. Main application directions

At the end of the 1970s, machine-visual technology began to be applied to the quality testing and grading of agricultural products[4]. The rapid development of computer software and hardware technology and the automation industry has greatly promoted the breakthrough of machine vision technology in the field of agricultural machinery and equipment. In the agricultural machinery and equipment required for the production and processing of agricultural products, machine visual technology can be used to realize the digitization of the production process, so as to make the production process more objective and standardized: growth process monitoring, fine agriculture, quality inspection, grading, and automatic navigation.

3.1. Application in inspection and sorting machinery

Machine vision technology was first applied to quality inspection and quality grading equipment for agricultural products[5]. The manual processing of agricultural products such as melons, fruits, beans, and vegetables, which are huge after harvest, is not only time-consuming and laborious but also difficult to guarantee the results of sorting and inefficient. In practical applications, according to the basic physical characteristics such as the form and color of the outer surface of agricultural products, the grading standards are preset[6,7], relying on machine vision technology to process images of agricultural products for loss-free inspection, and the control actuator completes automatic grading, which effectively improves production efficiency and reduces labor and time costs. Based on machine vision technology, Wang et al.[8] designed an automatic, rapid, and loss-free detection and grading machine for jujubes, collected comprehensive index information such as jujube fruit size, color, and external damage, and used pneumatic execution to complete the grading. The test results show that the accuracy of the comprehensive index test is above 92% and the yield is 550 kg/h, which meets the requirements of jujube and fruit production. Sofu et al.[9] developed a real-time processing apple automatic sorting and quality detection system through the capture and analysis of four images of apples on the conveyor belt to obtain different types of apple color, size, weight, and fruit really affected by scabs. The effects of stains and decay are sorted. The results of the test show that the device can sort 15 apples per second, with an average accuracy rate of 73% to 96%.

Different from the traditional RGB imaging system[10,11] that only analyzes external characteristics, hyperspectral imaging technology can analyze the physical structure and chemical composition of agricultural products, and related research has gradually heated up in recent years. Shan et al.[12] combined hyperspectral image processing and spectral information through an image scan to detect the surface of the apple and the detection of sugar content. The detection of comprehensive quality inside and outside the apple was realized, the screening efficiency was improved, and the comprehensive detection rate reached 92.6%. Zhang Dongyan et al.[13] developed the field scanning imaging photo spectral spectra by themselves; the canopy high-light spectroscopy images of pots and fields were obtained closely; and the spectra of leaf fragments with different layers of jade and rice were accurately extracted to construct a spectral prediction model for chlorophyll content in jade rice. The validation results indicate that the RMSE error between the prediction and the arms error of the validation model is 1.8. Under different vegetation coverages (potted-field), jade rice plants have achieved very good results, the precision of the mold is relatively high, and it has great development potential.

3.2. Application in agricultural production automation equipment

The growth and cultivation of crops is a relatively long and complex process, and in modern precision agriculture, it is necessary to adjust the temperature[14], humidity, moisture, and light intensity[15] of the growing environment in a timely manner based on the growth conditions of crops, such as length and color, so as to provide a suitable external environment for the growth of crops[16]. Machine vision technology meets the requirements of long-term stable monitoring, can timely collect crop growth images, analyze the images to give quantitative crop growth information, and provide information support for delicate crop cultivation[17]. Ma et al.[18] designed and constructed a plant growth information measurement and analysis system based on image processing technology, realized the lossless monitoring of multiple chrysanthemums over a long period of time, and improved the accuracy of detection through improved calculations, which is the theoretical basis for the growth information provision technology of continuous untouched monitoring plants. Jiang et al.[19] used the seedling method of double-station to construct melons, eggplant, vegetables, and vegetables to graft machines on such issues as low efficiency, low survival rate, and difficulty in guaranteeing quality. The results of the test show that the success rate is similar to the grafting effect of human labor, but the speed is increased by 5 to 6 times, which satisfies the requirements of the automation technology of the factory. Yang et al.[20]

proposed a seedling acupuncture disc positioning and detection system for grafting seedlings using automatic transplanting machines, which obtained matrix depth and three-dimensional shape information for each hole by overcutting images and analyzing the depth of vectors. The results of the test show that the system can complete accurate identification quickly and steadily, and be satisfied with automatic movement control requirements for planting robots. Gongal et al.[21] have developed a new sensor system platform that analyzes and estimates apple production by obtaining side images of apple trees in tunnel structure illumination. The results of the trial show that the overall accuracy of the device has reached 82%, which is expected to provide a basis for apple orchards to accurately and reliably estimate apple yields.

3.3. Application in farmland pest control equipment

Most crops grow in an open-air environment and come into direct contact with soil or water sources, making them susceptible to pests and diseases and the threat of competitive growth by weeds[22,23]. These pests and diseases will not only affect the yield of agricultural products, but also the traditional large-scale application of drugs, which will reduce the quality of agricultural products to a certain extent. The machine vision system can efficiently complete the detection and identification of weeds, diseases, and insects, and meet the requirements of precision agriculture. At the same time, the complexity of the agricultural environment and the variability of the work itself[24] determine the possibility and potential of machine vision agricultural equipment to operate for human labor.

Li et al.[25] developed a rapid infestation of citrus full-claw mites based on optical measurement techniques that quickly, accurately, and non-destructively detected the degree of damage to fruit trees on the spot by measuring the reflectivity of fruit and vegetable canopy leaves to red light and near-infrared light. The test showed that the results were stable and that there was a high correlation between the instrument infusion results and the actual number of pest eggs. Han and He[26] designed a set of field pest remote automatic identification systems, transmitted pest photos through the 3G network, and built a support vector machine classifier after extracting characteristic values such as shape and color. The test results show that the average accuracy rate is 87.4%, which enables rapid real-time identification and diagnosis, which can provide timely and accurate insect information for the control of field pests. Zhang et al.[27] researched and developed a near-infrared hyper spectral imaging system of 900 to 1700 nm. Through the comparative analysis of hyper spectral images of rice weevils, the application area is proposed. The domain growth method distinguishes the live food insects, and then accurately counts the density of the out-of-storage pests. The test results show that after 2 days of death of self-grain insects, the system completely and correctly identifies live insects and dead insect samples, which provides a scientific basis for decision-making for the comprehensive prevention and treatment of grain storage pests.

3.4. Applications in picking machinery

Fruit and vegetable picking is the most time-consuming and labor-intensive ring in the agricultural product industry chain[28], and the diversity of fruit and vegetable surfaces and shapes, the growth position, and the randomness of the direction all require a large amount of recognition and mobility work from the harvesting staff. It limits the efficiency of the harvesting work, and the automatic harvesting and unloading equipment combined with the visual technology of the machine has great potential for development. At the same time, in order to adapt to the complex and changeable work environment, the visual positioning system of the machine has developed from the initial monocular vision to the bi-eyed[29,30] and even the multi-eye[31] vision, effectively realizing the precise positioning of reality in three-dimensional space. Xiong et al.[32] designed and manufactured a test platform to simulate fruit body disturbance during the picking process of lychee, combined with the simulated motion parameters of the vibration platform, and proposed a three-dimensional image reconstruction method for collecting the disturbed state of the lychee. The test results showed that the error of the spatial positioning depth value was less than 6cm, and the mechanical hand could achieve effective harvesting. It provides guidance for practical work. Feng et al.[33] designed a laser vision system for apple extractors, using a laser rangefinder to complete a three-dimensional scan of the target scene. The resulting distance image is easy to analyze, including the fruits, the spatial characteristics of the branches and leaves, and the layers between each other, and is not affected by the natural change of light lines. Provides a richer picture of pattern information for the automation and mechanization of fruit and vegetable picking.

3.5. Application in navigation and positioning of agricultural machinery

With the rise of large-scale agricultural operations, production modes such as planting specialized households and mechanized collective farms have developed day by day, and the traditional two-dimensional operation of the ground has been unable to meet the demand for quantity and quality at the same time. The process of application and other processes has been transformed into three-dimensional space and has become an important part of the agricultural machinery system[34–36]. In 2016, the agricultural application of the Beidou navigation system independently developed in China was developed by the Xinjiang Construction Corps and Heilongjiang Agricultural Reclamation in all parts of the country, and emerging technologies such as unmanned driving, high-precision positioning and navigation, and system monitoring have made traditional agricultural production full of the charm of scientific and technological modernization.

Ding et al.[37] designed a combined harvester machine visual navigation control hardware system that accurately detects the boundary line of the harvest area according to the rotation projection algorithm and the histogram fusion algorithm. The results of the wheat field test show that the variation range of cut within the normal working speed range is 0.18 m or less, and the control system has good anti-interference performance. Guo and Chen[38] developed a field autonomous mobile weeding robot based on machine visual navigation, based on regional images and color characteristics, and based on a modular control algorithm to achieve autonomous navigation and weed identification by weeding robots. The results of the test show that the robot can complete the navigation task well, and the modular control effectively improves the anti-interference ability, stability, and reliability of the navigation control. Chen et al.[39] constructed a multi-sensor integrated navigation and positioning system based on GPS and machine vision, using GPS and machine vision to obtain absolute position information and navigation reference lines of navigation vehicles, respectively, and carry out filtering and comparative analysis of combined navigation and positioning. The experimental results show that the precision and robustness of the positioning system have been improved, the positioning curve has been smoothed, and the drawbacks of single sensor positioning have been overcome.

4. Current problems

China is a large country with a population based on agriculture, and many experts and scholars have long been devoted to the application and study of machine vision technology in the field of agricultural equipment, and have made considerable progress in many directions. The variety of agricultural machinery products has been constantly increasing, and the production capacity has been increasing day by day. However, in some aspects, there are still many problems that need to be solved urgently in the actual environment in which equipment combined with machine vision technology is applied in fine agriculture to the field, and it is necessary to improve and improve it in future research and production work.

1) The agricultural production environment is complex, and many working objects lack regularity. Agricultural production areas are changeable[40], and the growth conditions such as temperature, light, and wind speed are different from each other and cannot be controlled. At the same time, the shape, size, color, and other appearance characteristics of various types of work objects vary greatly, and much

intellectual agricultural equipment is only suitable for agricultural objects in a specific environment and has certain limitations[41,42].

2) Image identification and analysis still need to be continued. At present, most of the research is to deal with static and two-dimensional pictures, and the anti-interference ability is poor, which cannot meet the requirements of parallel real-time processing. It is urgent to improve the speed, accuracy, and accuracy of processing[43]. Machine vision technology belongs to the multidisciplinary interdisciplinary field, which objectively increases the difficulty of research and engineering costs.
3) Limitations of hardware conditions. At present, the scientific and technological content and economic cost of image recognition systems, central processors, and terminal enforcement agencies are still relatively high, which limits the promotion and use of complete sets of intellectual systems[44,45]. In terms of automatic picking, diseases and pest detection, etc., due to cost factors, the system has problems such as slow operation speed and low processing accuracy[46], and large-scale engineering applications have not yet been realized.
4) Restriction of agricultural production mode. At present, China's agricultural production is still dominated by decentralized operations, many mountainous and hilly areas are not suitable for large-scale mechanization, and it is more difficult to popularize the equipment of intelligent agriculture. At the same time, relying solely on agricultural machinery subsidies for development is not a long-term solution, and it is necessary to raise the level of awareness of the peasants as a whole and actively guide the healthy development of the agricultural machinery market[47].

5. Outlook

In China, the application of machine vision technology began in the 1990s. After more than 20 years of development, machine vision systems have been widely used in many fields of agricultural production, saving a large amount of human and material resources and improving production efficiency. Improving agricultural engineering applications that improve machine vision technology requires simultaneous efforts from both the software and hardware aspects. Software aspects and image recognition calculations are the important bases for implementing machine vision. Improving existing arithmetic, improving the processing efficiency and reliability of algorithms[48], and using them in conjunction with neural networks[49–51] to enhance the robustness of calculations and support for dynamic three-dimensional images can further open up and develop the application of machine visual technology in agricultural machinery and equipment. In addition, the improvement of the hardware aspect comes from the improvement of the production level, the enhancement of computing power, the improvement of the discrimination rate, the acceleration of scanning speed, and the enhancement of software functions[52], such as the combination with the Beidou navigation system. The use of machine vision technology to detect farmland information and realize intelligent navigation will become an important research hot spot for the unmanned use of agricultural machinery and equipment[47]. Wisdom and agricultural equipment undoubtedly have an extraordinary broad prospect in front of China's world's largest agricultural market. With the development of China's processing and manufacturing industry and the gradual upgrading of the advanced manufacturing industry, agricultural equipment combined with machine visual technology will surely go from the low end to the high end, helping the rapid advancement of the process of agricultural modernization.

6. Conclusion

With the perfection of supporting infrastructure and the accumulation of technology and funds, the research and application of machine vision technology in the fields of sorting agricultural products, monitoring of growth processes, control of pests and diseases, picking machinery, and automatic navigation and positioning have developed vigorously. The rapid development of advanced technology represented by machine-visual technology has provided new impetus and possibilities for the transformation and upgrading of China's agricultural industry and the steady progress of precision agriculture.

Agriculture is a fundamental issue that has a bearing on the national economy and the people's livelihood, and the steady development of agricultural modernization has a bearing on the country's long-term peace and stability. Since the 21st century, agricultural labor has been continuously transferred to other industries, and the problems of structural shortages and the gradual aging of the industrial population have become increasingly serious. Machine vision technology can improve the mechanization level of agricultural production, liberate labor, and help agricultural production move steadily towards modernization, automation, and intelligence.

Conflict of interest

The authors declare no conflict of interest.

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