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Review

Research Hotspots and Frontier Prospects in the Field of Agroforestry Picking Robots in China—Cite Space Bibliographic Analysis

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Abstract: The research on picking robots is vital to the transformation and upgrading of the agroforestry industry and the revitalization and development of rural areas. This paper examines the research field of agroforestry picking robots by meticulously combing and analyzing 623 CNKI and 648 WoS core literature from 2004 to 2022 selected in China Knowledge Network (CNKI) and Web of Science (WoS) databases using Cite Space 6.1R3 software. The analysis includes the quantity of literature, issuing countries, organizations, keywords, keyword clustering, emerging terms, etc. On this basis, research hotspots in the field of agroforestry picking robots are identified, such as research based on the identification of picking targets, the control of motion planning, structural design and simulation, and the planning of walking paths. This paper analyzes and discusses these research hotspots and main lines, providing a reference for future studies in this field. This bibliometric approach can provide comprehensive literature information for research in related fields, as well as identify and summarize the major research hotspots in a shorter time, allowing new researchers to enter the field more quickly and obtain more valuable scientific information.

Keywords: smart picking; visual analysis; bibliometrics; knowledge graph; literature review

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Citation: Jia, N.; Zhang, H.; Gao, H.; Liu, J. Research Hotspots and Frontier Prospects in the Field of Agroforestry Picking Robots in China—Cite Space Bibliographic Analysis. *Forests* **2023**, *14*, 1874. https://doi.org/10.3390/f14091874

Academic Editor: Rodolfo Picchio

Received: 5 August 2023
Revised: 9 September 2023
Accepted: 12 September 2023
Published: 14 September 2023

1. Introduction

Agroforestry picking robots are robots utilized in agriculture and forestry for the purpose of harvesting fruits, vegetables, and other commodities. As a crucial element in the production chain of crops and forest products, harvesting has a significant impact on costs, efficiency, and quality [1–3]. Human picking expenses can make up between 50 and 70 percent of overall production costs [4], and various picking methods, tools, and processes can also affect picking efficiency and fruit quality or even cause mechanical harm to both fruits and trees [5,6]. With rising labor costs, labor shortages, and other issues gaining prominence, agroforestry picking robots have emerged as a crucial means of modernizing agricultural and forestry selecting technology and enhancing production efficiency [7]. The research and development of agroforestry picking robots has become the focus of domestic and international research institutions and businesses.

In 1968, American scholars Schertz et al. [8] pioneered the application of robotics to citrus harvesting, establishing a precedent for the study of agroforestry harvesting robots. Currently, agroforestry picking robots have been the subject of extensive research and application on a global scale, and large-scale agribusinesses in some developed nations and regions have developed and deployed robust and stable picking robots [9–12]. China's research and development of agroforestry picking machines began in the mid-1990s and has yielded fruit. For instance, Lu [13] developed the pinecone picking robot, which successfully solved the problem of picking pinecones growing at high altitudes, with efficiency increasing by 30–50 times compared to manual labor. Xiong et al. [14] created a multi-purpose picking automaton with an 80 percent success rate for harvesting lychees and mandarin oranges. In recent years, the Chinese government has issued a number of policies, such as the Development Plan for Agricultural Mechanization and the Guiding Opinions on Accelerating the Development of the Robot Industry, which explicitly propose to promote the synergistic development of mechanization and intelligence in agriculture and forestry. Meanwhile, China has a wide variety of agricultural and forestry products and an urgent demand for mechanized picking, which provides the impetus for these policies [15].

There are currently numerous technical challenges in the study of agroforestry picking robots, which primarily involve the following five aspects: biological environment perception, cognitive decision control, efficient and precise operation, autonomous navigation and walking, and eye-brain-hand-foot synergy [16]. With the development of artificial intelligence, cloud computing, the Internet of Things, and other technologies, the intelligence and automation of agroforestry picking machines are increasing, bringing about significant changes and new opportunities for agriculture and forestry production [17–19]. The research on agroforestry picking robotics encompasses a wide range of disciplines, including mechanical design, electronic information, control technology, machine vision, etc. and is thus both comprehensive and interdisciplinary. The traditional approach suggests that it is necessary to peruse a great deal of relevant literature to comprehend the research status and development trend of the field [20]. However, as the discipline continues to grow and expand, so does the number of related papers, patents, and other publications. Reading thousands of documents in a brief period of time is unrealistic for novice researchers. In order to summarize the current research status and predict future development trends, it is crucial to analyze the existing literature swiftly and precisely using scientific methods. A review of the research in the field of agroforestry harvesting robots can aid in gaining a comprehensive understanding of the most recent research dynamics and technological trends in this field, as well as provide guidance for future research and applications.

Bibliometrics is a technique for analyzing literature based on mathematics and statistics [21]. Through screening and processing a large amount of literature, researchers can discover the potential knowledge value, which can qualitatively and quantitatively evaluate and predict the current status and development trend of research in the field, thereby reducing the reading burden of scientific research workers and, in turn, increasing their productivity [22]. Information visualization analysis is a technique for presenting the complex relationship among the literature in graphs, infographics, and other intuitive forms [23]. Through visualization analysis, a scientific knowledge map with a hierarchical structure and significance can be created, allowing researchers to gain a clearer comprehension of the development trend and future direction of their field [24]. Cite Space is a software for literature analysis that combines bibliometric analysis and information visualization [25]. The software, which was developed by Dr. Chen C of Drexel University, is written in Java, adheres to the guiding principle of metrological science, and is supported by data visualization technology [26]. With its powerful bibliometric analysis and visualization functions, to a certain extent, it reduces the influence of the researcher's subjective judgment so that the analysis results are more scientific and objective. As a result, it has been widely employed in the fields of archive management, medicine, geography, etc. [27–29]. In recent years, Cite Space has been utilized in green ecology, agricultural product circulation, forestry big data, and other agriculture and forestry industry-related disciplines, but it is rarely used in picking robotics [30–33].

Therefore, utilizing the bibliometric analysis function offered by the Cite Space software [34], this paper analyzes the global research situation, research institutions, and keywords in the field of agroforestry picking robots research. Visual network mapping of the aforementioned research contents is also conducted. This paper shows the international development process and content evolution of agroforestry picking robots research, illustrates the research hotspots and dynamic frontier in this field, and predicts the future development direction in order to serve as a reference for the relevant research in China.

2. Data Processing and Research Methods

2.1. Data Sources and Search Strategies

Chinese literature was selected from the China National Knowledge Infrastructure (CNKI) search platform, where the search mode was journal search, the subject term was “picking robot”, the source category was “EI” and “Chinese core journals”, the search time was from 1 January 2004 to 31 December 2022, excluding advertisements, patents, repetitive literature, unpublished articles, industry articles, and literature unrelated to agriculture and forestry robotics. The final CNKI database eliminated 623 pertinent documents. The English literature was retrieved from the Web of Science (WoS) search platform using “core collection” as the search mode, “Picking robot” as the subject term, and “Article” or “Review”, as the type of literature. Under the “Web of Science Categories” tab, the following categories were selected: “Robotics”, “Forestry”, “Agronomy”, “Agricultural Engineering”, “Agriculture Multidisciplinary”, “Plant Sciences”, “Multidisciplinary Sciences”, and “Computer Science Interdisciplinary Applications”. The search duration was comparable to that of Chinese literature, and 648 articles were recovered after irrelevant literature was eliminated. In this study, the tag “PEOPLES R CHINA” under “countries/regions” was specifically chosen as the standard source identifier for publications originating from China within the selected English literature database. According to this criterion, a total of 138 English-language papers related to China were identified. Meanwhile, the remaining 510 papers were recognized as publications in English.

2.2. Research Methods

This paper used Cite Space software for research and analysis, which has strong bibliometric analysis and information visualization capabilities. It can generate a knowledge graph with a clear framework structure, which aids researchers in intuitively analyzing the relationship between knowledge structure and law evolution in related fields [35]. Compared with HistCite, Bibexcel, Pajek, TDA, and other software of the same type, Cite Space is stronger in the pre-processing and normalization of data, and the steps of each operation in the whole process of constructing a knowledge graph are flexible, which can highlight the core items. It is also very suitable for the analysis of emergent monitoring, collaborative relationships, co-citations, etc. In addition, the software pays great attention to the updating and upgrading of the version and is free for researchers to use [36,37]. We imported the recovered Chinese and English documents into the software using the Cite Space 6.1R3-specified format, selected node types, such as country, organization, and keywords, and assigned the time slice to one year. According to the established parameters, the literature release trend, release country, institutional cooperation network, etc., were analyzed, and the fundamental situation of the agricultural and forestry harvesting robotics research field was described. The co-occurrence analysis, cluster analysis, and emergence analysis of the keywords in this research field were conducted, and the development of the field of agroforestry harvesting robots was categorized by combining the manual information from the literature in order to discuss the research hotspots and future development trends in this field.

3. Visual Results Analysis

3.1. Analysis of Annual Publication Volume

The number of annual publications in the field of agroforestry harvesting robots reflects, in part, the rate of progress and shifting research trends [38]. Statistics indicate that during the studied period, the number of articles published in both Chinese and English increased, indicating that harvesting mechanization is an international concern. Recent research in the field of agroforestry harvesting robots can be loosely divided into three phases based on the number of publications at various stages (Figure 1).

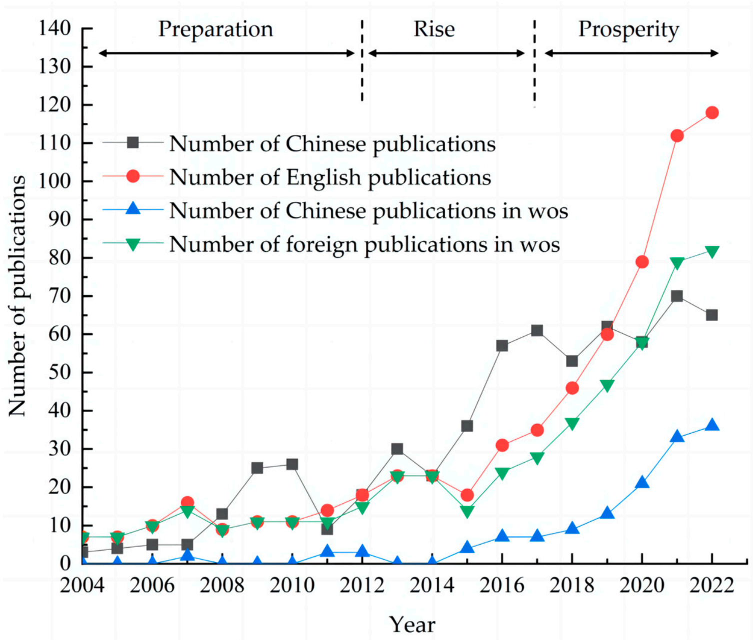

Figure 1. Publication year distribution and publication quantity statistics chart for research in the field of agricultural and forestry picking robots—including Chinese and English literature.

From 2004 to 2012, harvesting robotics research was in its infancy, with an average of 12 and 11.5 articles per year in English and Chinese, respectively, accounting for 16.7% of the total number of publications, and the numbers of English and Chinese publications were quite similar.

The period from 2012 to 2017 was the growth stage, the annual average number of articles published in both Chinese and English increased significantly, ending at 43.3 and 29.3, respectively, accounting for 26.5% of the total number of articles published, indicating that the research in this period was in a high growth state, and the number of articles published in Chinese was higher than that published in English. High growth during this era can be attributed to China's high-end equipment manufacturing industry's "Twelfth Five-Year Plan" in 2012 and "Made in China 2025" in 2015.

The period from 2017 to 2022 was a period of significant growth in the field of harvesting robotics research, with the average annual number of articles published in English and Chinese increasing to 61.6 and 83, respectively, accounting for 56.8% of the total number of articles published, which is especially significant after 2019. Although English significantly outnumbers Chinese in terms of overall publication volume, the increasing proportion of Chinese publications in English demonstrates that Chinese researchers are increasingly focusing on international exchange and submitting their articles to English journals in order to engage in academic exchanges with international colleagues, increase the visibility of their research results, and continue to increase their international influence.

3.2. Analysis of Country Cooperation Networks

The analysis of national collaboration networks in the literature can reflect the distribution of scientific authority in the field of agroforestry harvesting robotics research and their international collaborative relationships [39]. In this study, a total of 648 papers were filtered from the WoS database and imported into specialized analytical software. Within the software, "country" was selected as the node parameter for network analysis, subsequently generating Figure 2 and Table 1 to display the pertinent data. It is worth noting that, when handling papers involving multiple authors from different countries, the analysis solely considered the nationality of the first author in order to maintain consistency and accuracy in the statistical results.

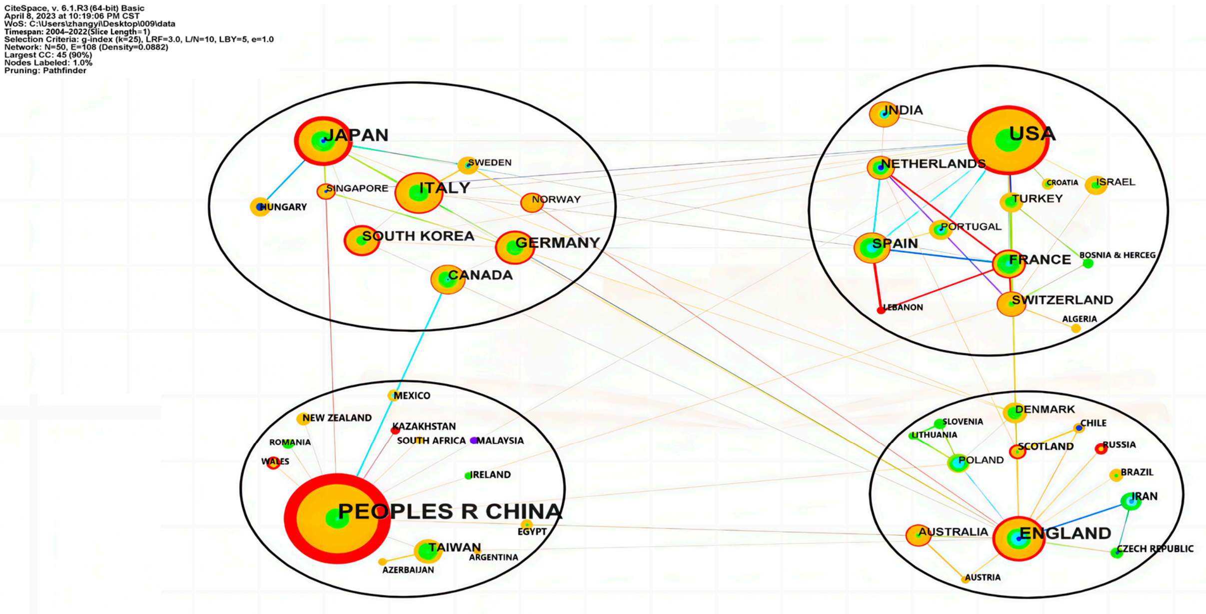

Figure 2. Network map of collaboration among countries in English literature.

Table 1. Top 10 countries in the number of English literature publications.

Ranking	Country	Count	Percentage (%)	Centrality
1	China	167	22.6	0.48
2	USA	114	15.4	0.40
3	Japan	57	7.7	0.15
4	Britain	47	6.4	0.61
5	Italy	39	5.3	0.05
6	Germany	29	3.9	0.04
7	Spain	21	2.8	0.04
8	Korea	21	2.8	0.01
9	Canada	20	2.7	0.01
10	France	19	2.6	0.01
11	Others	204	27.8	/

Figure 2 depicts the mapping of national collaboration networks in the English literature, which identifies the four most prominent global collaboration teams. China's research team does not collaborate closely enough with its own members, and it also collaborates inadequately with other teams. In contrast, the collaboration teams led by the United Kingdom, the United States, and Japan have closer internal communication and cooperation and are progressively forming a network of collaboration. Simultaneously, cooperation between various teams is carried out gradually, particularly between the United States and Japan-led teams. Table 1 displays the top ten countries in terms of the number of publications in English literature, which are primarily distributed in Asia, America, Europe, and other regions rich in agroforestry resources. China, the United States, Japan, and the United Kingdom have a large number of publications and a high degree of betweenness-centrality, indicating that in addition to their own scientific contributions, they play a key role in international cooperation. Although China has the most articles, its betweenness-centrality is significantly lower than that of the United Kingdom. In light of this, China must increase international cooperation and enhance the quality and impact of its scientific research.

3.3. Analysis of Institutional Cooperation Networks

Institutional cooperation network analysis can aid researchers in comprehending the cooperation relationships between research institutions and provide cooperation benchmarks for the field's future development [40]. The results of the visualization and analysis of the Chinese institutional cooperation network in the field of agroforestry harvesting robotics research are depicted in Figure 3.

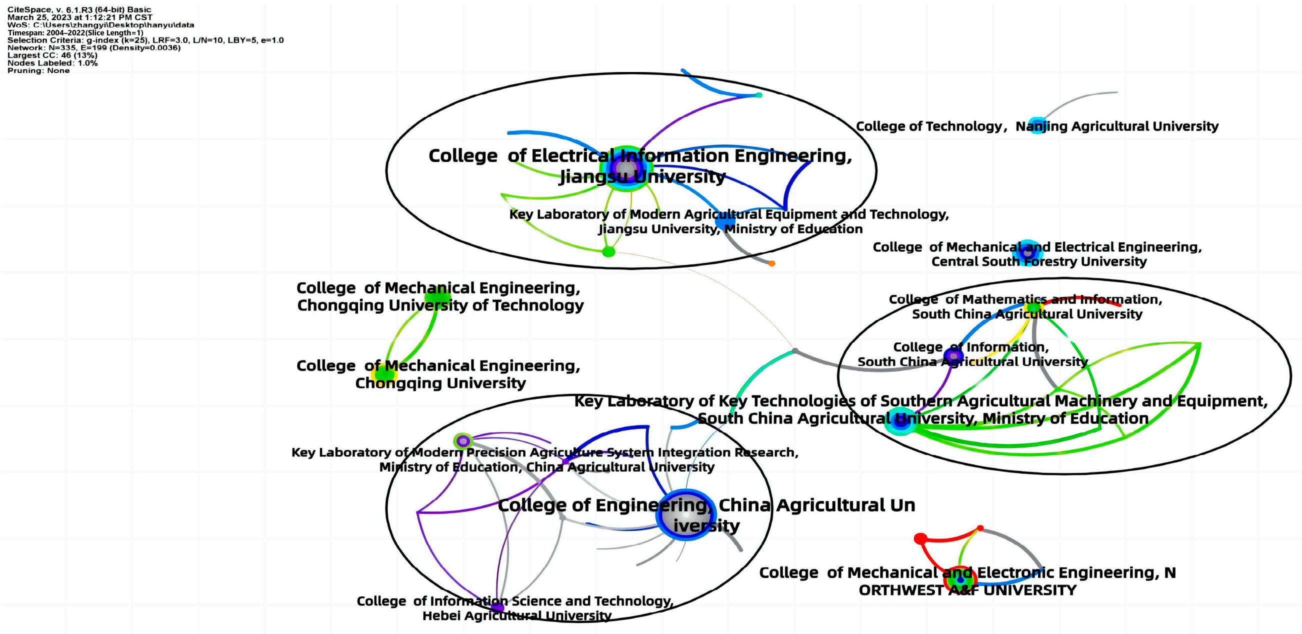

Figure 3. Network map of collaboration among institutes with published papers in Chinese literature.

From the node connectivity layout in the chart, it is evident that the primary contributors to research in the field of agricultural and forestry harvesting robots in China are multiple higher education institutions specializing in agriculture and forestry. However, collaborations among these institutions appear to be not yet well-established, indicating a certain degree of limitations in cooperative efforts. Conversely, there is a higher density of collaboration within individual universities among different research units. Taking, for example, China Agricultural University (CAU), Jiangsu University (JSU), and South China Agricultural University (SCAU), the number and thickness of the connecting lines suggest that the internal collaborations among various research units within these schools are relatively tight-knit.

The top ten Chinese high-publishing institutions in terms of the number of articles published are presented in Table 2. In addition, the Key Laboratory of Key Technology of Southern Agricultural Machinery and Equipment of the Ministry of Education of South China Agricultural University published 16 documents. In the meantime, the betweenness-centrality of the aforementioned institutions is extremely low, indicating that domestic institutions with the capacity to serve as a bridge and a high degree of influence have not yet been established in this field. To improve China's research level and technological innovation capacity in this field, cooperation between domestic institutions should be further strengthened, stable cooperative relationships should be established, and the integration and collaboration of research forces should be enhanced.

Figure 4 depicts a map of the collaborative network of research institutions for robotic agroforestry harvesting. The figure identifies the three most prominent collaborative teams in the world, while inter-institutional collaborations exhibit stark differences. The two principal Chinese research teams, commanded by SCAU and Northwest A&F University (NWAFU), have relatively few internal collaborations with strong foreign institutions, and their connection is insufficient. In contrast, the team comprised of Osaka University (OU), the Massachusetts Institute of Technology (MIT), the National Institute of Advanced Industrial Science and Technology (AIST), and the University of Tokyo (UT) has particularly strong internal connections. SCAU, NWAFU, and OU ranked first, second, and third, respectively, among the top 10 institutions that published the most papers in this field (Table 3). The betweenness-centrality of these institutions was found to be greater than 0.1 for AIST, UT, and SCAU, indicating that these three institutions are important intermediaries in promoting cooperation between domestic and foreign research institutions and have a high research quality and influence. Even though SCAU has the most publications, its betweenness-centrality is considerably lower than that of the AIST. In light of this, we propose that domestic research institutions should pay more attention to strengthening international cooperation while simultaneously strengthening domestic cooperation in order to further enhance the quality of scientific research and increase their international influence.

Table 2. Top 10 institutions in Chinese literature publication volume.

Institution	Count	Centrality	Year
College of Engineering, China Agricultural University	26	0.02	2004–2012, 2012–2016, 2018
College of Electrical and Information Engineering, Jiangsu University	26	0.01	2009–2010, 2012–2016, 2019
College of Mechanical and Electronic Engineering, Northwest A&F University	17	0.00	2012, 2014, 2017, 2019, 2022
Key Laboratory of Agricultural Machinery and Equipment in South China, Ministry of Education, South China Agricultural University	16	0.01	2011, 2013–2019
Key Laboratory of Modern Fine Agriculture System Integration Research of Ministry of Education, China Agricultural University	15	0.00	2008, 2010, 2013–2015, 2017, 2019
College of Mechanical Engineering, Chongqing University of Technology	15	0.00	2018–2020
College of Mechanical and Electrical Engineering, Central South University of Forestry and Technology	15	0.00	2012–2019, 2022
College of Engineering, Nanjing Agricultural University	13	0.00	2007, 2010–2012, 2014–2017
College of Informatics, South China Agricultural University	10	0.01	2012–2015
College of Mathematics and Informatics, South China Agricultural University	8	0.00	2017–2020, 2022

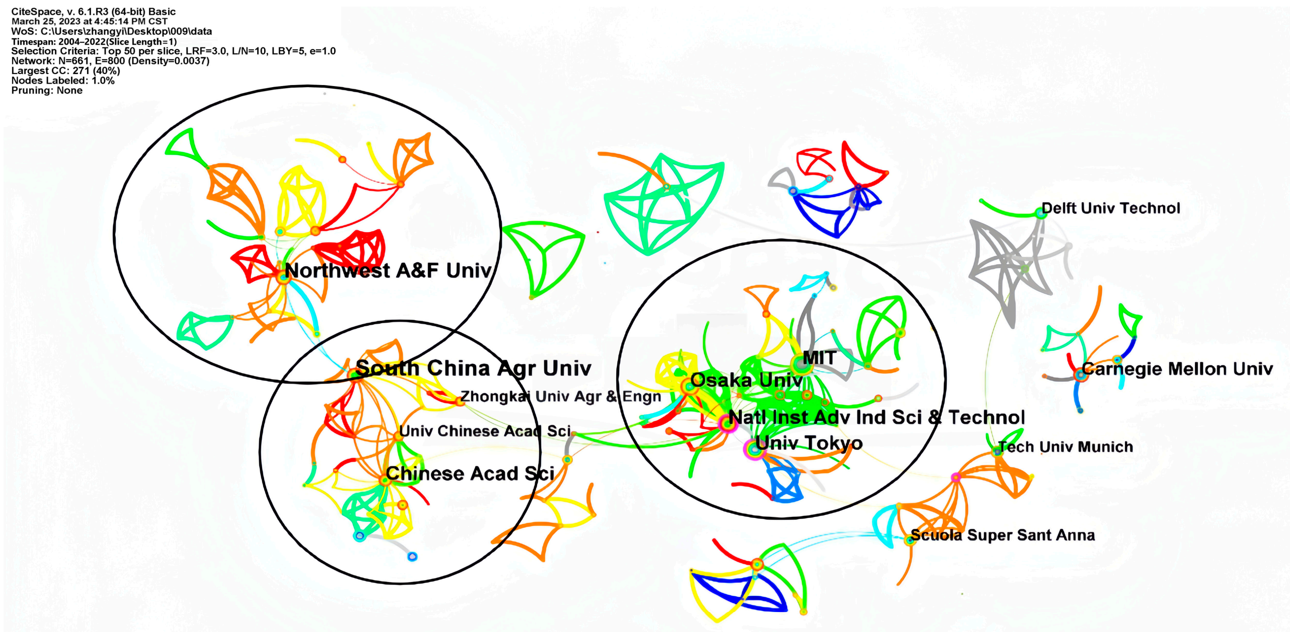

Figure 4. Network map of collaboration among institutes with published papers in English literature.

Table 3. Top 10 institutions in English literature publication volume.

Institution	Count	Centrality	Year
South China Agricultural University	18	0.10	2016, 2018, 2020–2022
Northwest A&F University	14	0.08	2015, 2019, 2021
Osaka University	13	0.03	2007, 2019–2022
Massachusetts Institute of Technology	12	0.06	2010–2012, 2017–2019
Chinese Academy of Sciences	11	0.06	2017, 2020–2022
Natl Inst Adv Ind Sci and Technology	11	0.15	2007, 2019, 2021–2022
Tokyo University	11	0.10	2005, 2007, 2015, 2018
Carnegie Mellon University	9	0.03	2005, 2012, 2015, 2017, 2021–2022
Technical University of Munich	8	0.02	2011, 2018
Ministry of Agriculture and Rural Affairs	8	0.01	2021

3.4. Keyword Co-Occurrence Analysis

Keywords are a distillation and summary of the core content of an article, and co-occurrence analysis of keywords is to take keywords as nodes to reflect the hot areas of research, research perspectives, and research methods within different time sequences through expansion, thereby demonstrating the inner connection of disciplines [41]. Figures 5 and 6 depict the co-occurrence network of keywords in English and Chinese agroforestry picking robots literature. Each node in the figure corresponds to a keyword, the size of the node represents the total frequency of the corresponding keyword, and the connecting line between the nodes indicates the existence of a co-occurrence relationship between two keywords, with the thickness of the connecting line proportional to the number of co-occurrences. Table 4 displays the results of the classification of the high-frequency terms in the literature.

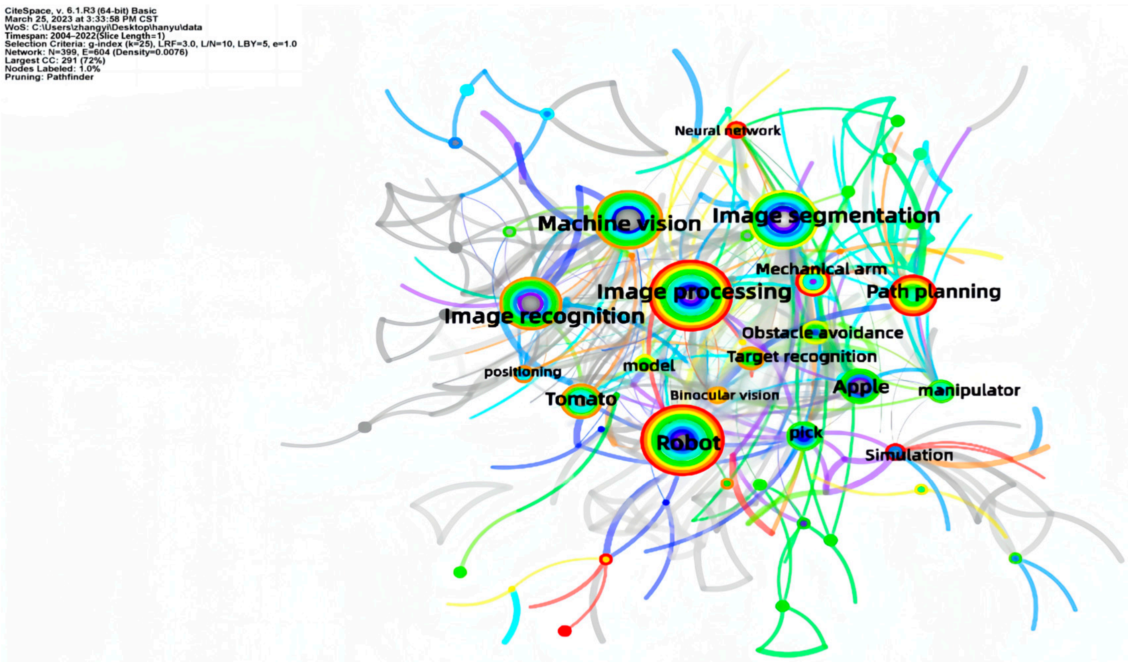

Figure 5. Network map of keyword co-occurrence in Chinese literature.

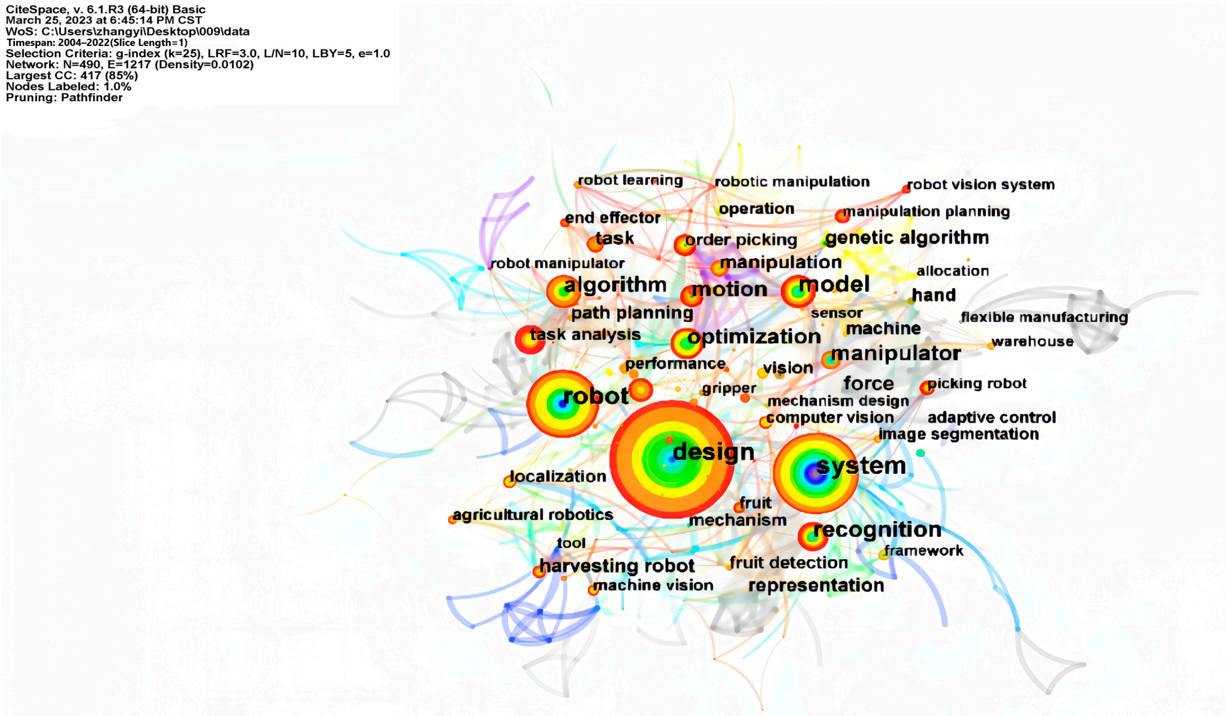

Figure 6. Network map of keyword co-occurrence in English literature.

Increasingly, Chinese literature research focuses on picking objects, primarily in fruits and vegetables (apples, tomatoes). The most prevalent research methods are vision technology (machine vision, image recognition, image processing, image segmentation) and simulation analysis (simulation). The primary focus of the research is the recognition of picking targets (image recognition) and the planning of the walking path of picking robots (path planning).

The English literature focuses more on the system Integration design (system, design, robot) of the picking robot, including the design of the end-effector system (manipulator, model), the design of the visual recognition system (recognition), and the design of the motion planning control system (motion, task analysis). Construction of optimization models and implementation of pertinent optimization techniques are typical research methods (optimization, algorithm, model). The English literature focuses more on the system integration research of choosing robots, as indicated by its keyword usage. The Chinese literature focuses on the identification of picking goals and the planning of walking paths, whereas the English literature focuses more on the design of system integration.

Table 4. Top 10 keywords frequency in Chinese and English literature.

Chinese Keywords	Count	Percentage (%)	Year	English Keywords	Count	Percentage (%)	Year
Robot	49	6.04	2005, 2009, 2011–2022	Design	90	7.99	2005, 2007, 2010–2022
Machine vision	44	5.43	2005–2012, 2014, 2016–2019, 2021	System	60	5.33	2007, 2012–2022
Image processing	35	4.32	2010, 2012–2022	Robot	54	4.80	2010, 2012, 2014–2021

Table 4. *Cont.*

Chinese Keywords	Count	Percentage (%)	Year	English Keywords	Count	Percentage (%)	Year
Image recognition	32	3.95	2009–2010, 2012–2015, 2017–2019, 2021	Algorithm	30	2.66	2008, 2011, 2013–2014, 2016–2022
Image segmentation	32	3.95	2004, 2006–2010, 2012–2018, 2020	Model	28	2.49	2005–2006, 2013, 2016, 2018–2022
Path planning	26	3.21	2016–2022	Recognition	24	2.13	2012, 2016–2017, 2019–2022
Apple	20	2.47	2010–2011, 2013, 2015, 2018–2019	Optimization	24	2.13	2009, 2012, 2016, 2018–2020, 2022
Tomato	17	2.10	2008, 2012, 2016–2017, 2019, 2021	Task analysis	22	1.95	2016, 2018, 2021–2022
Simulation	16	1.97	2008–2011, 2013, 2015–2016, 2018, 2022	Manipulator	20	1.78	2004, 2006, 2008, 2012–2013, 2015, 2017, 2019, 2021–2022
Mechanical arm	15	1.85	2013, 2016–2017, 2020, 2022	Motion	20	1.78	2005, 2012–2013, 2018, 2020–2022
Others	525	35.27	/	Others	754	33.04	/

3.5. Keyword Clustering Analysis

Keyword clustering analysis is based on term co-occurrence analysis and uses the Log-Likelihood Ratio (LLR) algorithm to analyze structural features, key nodes, and the degree of correlation between clusters to find research hotspots in the study domain [42,43]. Figures 7 and 8 depict the clustering network profiles of the Chinese and English keywords, with clustering modules (Q) of 0.6061 and 0.6494, showing a significant clustering structure (Q > 0.3). The mean contour (S) was 0.8822 and 0.8764, indicating that the clustering network was highly homogeneous (S > 0.5) and that the clustering results were reliable. Many instances of overlap between clusters indicated substantial inter-cluster interactions and a concentration of research hotspots.

The clustering labels of the Chinese and English literature are summarized in Table 5, which demonstrates that the hottest research directions in the field of agroforestry picking robots are primarily concentrated in four areas: picking target recognition, motion planning and control, structure design simulation, and walking path planning.

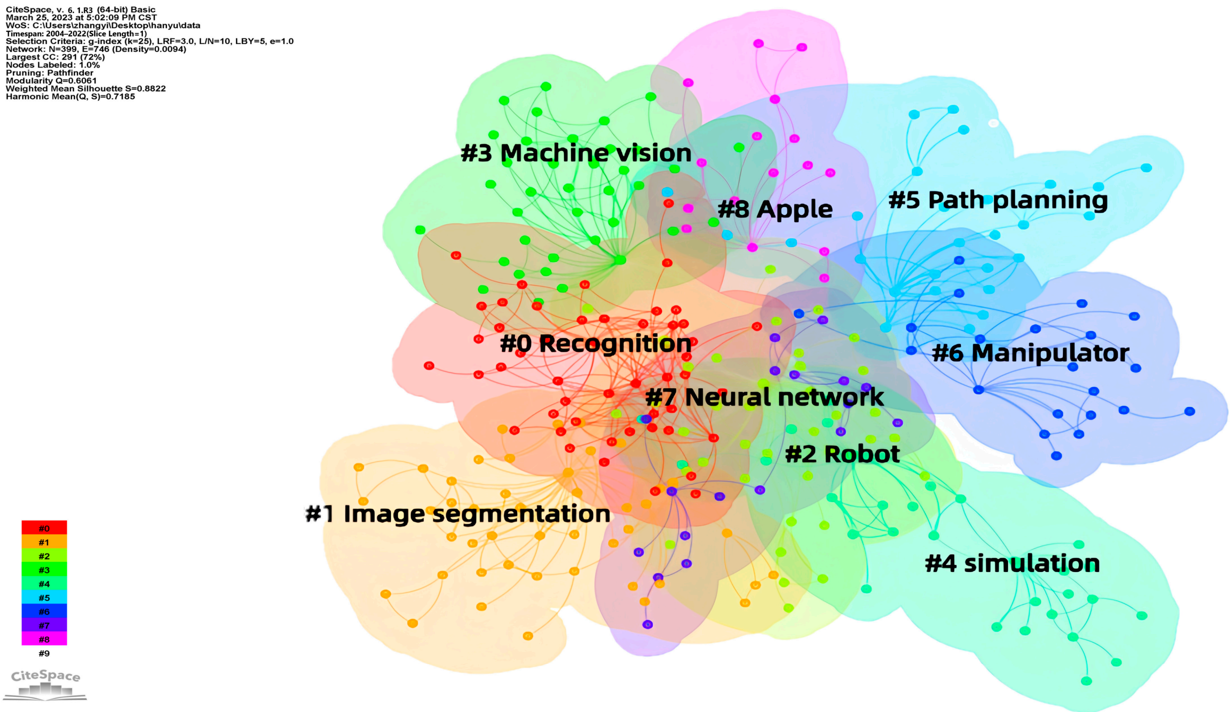

Figure 7. Network map of keyword clustering in Chinese literature.

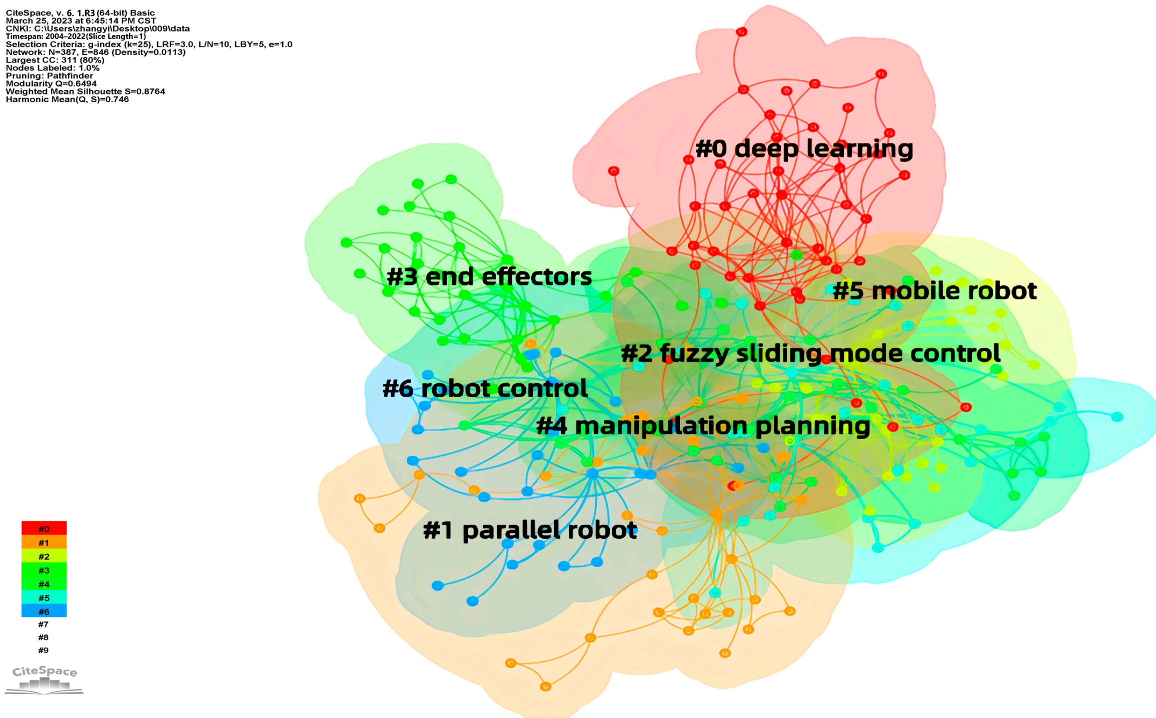

Figure 8. Network map of keyword clustering in English literature.

Table 5. Keywords secondary cluster analysis.

Research Direction	Included Clustering
Picking target detection	#0 recognition, #1 image segmentation, #2 robot, #3 machine vision, #7 neural network, #8 Apple, #0 deep learning
Motion planning control	#5Path planning, #7 neural network, #0 deep learning, #2 fuzzy sliding mode control, #4 manipulation planning, #6 robot control
Structural design simulation	#4Simulation, #6manipulator, #7 neural network, #0 deep learning, #1parallel robot, #3 end effectors
Walking path planning	#3 machine vision, #5Path planning, #7 neural network, #0 deep learning, #5 mobile robot

3.6. Keyword Emergent Analysis

Emergent terms are keywords that unexpectedly develop in a field and garner considerable attention. The examination of emergent terms can help pinpoint the field's research frontier [44]. Table 6 displays the outcomes of the Chinese keyword emergence investigation. The term with the highest occurrence rate is apple (5.99), and the years covered are 2010–2013, showing that the earliest research on agroforestry picking robots concentrated mostly on apples as the picking item. In recent years, the most prominent terms include path planning, deep learning, positioning navigation, and obstacle avoidance, where positioning navigation is to determine the robot's real-time location information while walking, and obstacle avoidance is to avoid dynamic and static obstacles, such as pedestrians, trees, and other operating machinery, to ensure human and machine safety. The ideal path for the picking robot is ultimately plotted using location navigation and obstacle avoidance in conjunction with sophisticated algorithms to achieve autonomous navigation, which is the cutting edge of research in this sector. Zhang et al. [45] combined Bei Dou navigation (BDS) and inertial navigation (INS) and optimized it with Kalman filtering and the bee colony algorithm, which significantly enhanced navigation and positioning accuracy. Chen et al. [46] proposed an obstacle avoidance path planning algorithm based on third-order Bessel curves that enhanced the real-time character of path planning.

Table 6. Analysis results of the top 10 emergent keywords in Chinese literature.

Keywords	Strength	Begin	End	2004–2022
Image segmentation	2.66	2004	2007	
Apple	5.99	2010	2013	
Identification	3.19	2014	2015	
Algorithm	4.74	2015	2017	
Positioning	3.33	2015	2016	
Grape	2.89	2015	2017	
Path planning	3.2	2016	2022	
Deep learning	3.99	2019	2022	
Obstacle avoidance	3.18	2019	2020	
Positioning and navigation	3.18	2020	2022	

Table 7 displays the findings from a keyword emergence analysis of English literature. Early research concentrated primarily on system integration design and that performance, soft robotics, and deep learning are the most recent emergent terms, indicating that the development of robots in the direction of flexibilization, and thus the improvement of picking performance, is the frontier of research in the field with the addition of artificial intelligence technology. The primary manifestations of flexibility are flexible materials and flexible control. To avoid damaging the produce, robots frequently use flexible materials, such as silicone, fabrics, particles, and memory alloys. Dong et al. [47] designed a flexible manipulator made of silicone and modeled after the oblique muscle design of the octopus limb that can effectively reduce the stress concentration during the movement of the manipulator when compared to a rigid manipulator. Regarding flexible control, the control method relies primarily on intelligent algorithms, such as fuzzy control, adaptive control, and related enhancement algorithms to enhance the control precision and stability of grasping. Tian et al. [48] proposed a method that combines adaptive neural fuzzy control with a sliding sensor to precisely control the gripping force of agricultural robots, addressing the issue of damage during apple picking.

Table 7. Analysis results of the top 10 emergent keywords in English literature.

Keywords	Strength	Begin	End	2004–2022
Iterative learning control	2.38	2007	2011	
Autonomous robot	2.12	2007	2013	
System	4.29	2012	2017	
Robot manipulator	2.39	2012	2013	
Parallel robot	2.39	2015	2017	
design	3.06	2016	2018	
Recognition	2.57	2016	2017	
Performance	2.76	2019	2022	
Soft robotics	2.7	2019	2020	
Deep learning	3.85	2020	2022	

In terms of hardware, sensors, such as pressure sensing and sliding sensing, are primarily implemented in conjunction with the control algorithm to achieve closed-loop control in order to regulate the manipulator's gripping force and prevent harm caused by improper gripping force. Kultongkham et al. [49] developed a robot for tomato picking using platinum-based silicone rubber material SF820. Force sensors were installed at the end of each finger of the robot to provide force feedback, and the control system adjusted the magnitude of the gripping force based on the signals from the feedback. This effectively mitigated the injuries caused by the inappropriate gripping force. By combining hardware and software, the robot's control is more responsive, and its grasping force is more uniform. Flexible design has become a focus of research in the development of robotic picking technology and is anticipated to become the future development trajectory for this field.

4. Research Hot Topics Discussion

This paper analyzes and discusses the research hotspots of agroforestry picking robots from four perspectives: motion planning and control technology, structural design and simulation technology, travel path planning technology, and visual recognition technology.

4.1. Research on Motion Planning and Control Technology

The motion control of the picking manipulator typically utilizes a master-slave bus-based distributed control mechanism [50]. The joint servo system adjusts the position and attitude of each of the robot's joints so that the end-effector can move to the picking target swiftly and precisely. The Proportional Integral Derivative (PID) algorithm is commonly used for position control of a single joint. This algorithm is extensively used because it is characterized by high control precision and rapid response [51,52]. To ensure the flexibility of the selecting manipulator, it is typically designed with a high degree of freedom, which introduces disruptive factors, such as high friction and kinetic coupling between the joints, thereby increasing the difficulty of control. In addition, standard PID algorithms no longer satisfy the practical requirements [53].

In order to address this issue, intelligent control algorithms, such as fuzzy control [54,55], neural network control [56], and adaptive control [57,58], as well as related improved algorithms, have been implemented into manipulator motion control. These algorithms are not dependent on the accuracy of the mathematical model of the controlled object, have a high level of robustness, and are able to maintain their original performance in the face of external disturbances and parameter changes. Consequently, they have garnered the interest and study of numerous scholars. Liu et al. [59] proposed a neural network-based adaptive control method to enhance the stability of the closed-loop system of manipulator control. Chen et al. [60] proposed an enhanced fuzzy neural network sliding mode algorithm, which effectively resolves the chattering issue of the apple-picking manipulator during grasping and compared it to the PID and sliding mode control algorithms. The control system's stability has improved.

4.2. Research on Structural Design and Simulation Technology

In the field of agricultural and forestry harvesting robots, the structural design primarily focuses on three core components: the chassis, the robotic arm, and the end-effector. The chassis serves as the foundational platform for the system, enabling the robot's mobility across diverse environments, such as gardens or forests. During the design phase, particular attention must be given to the adaptability of the chassis to various terrains: wheeled chassis is generally used for flat landscapes like gardens, whereas tracked chassis is preferred for more complex terrains like rugged forests. The robotic arm, a multi-joint structure with a high degree of freedom, allows for a variety of motion paths and posture configurations, accommodating different working environments and harvesting task requirements. The end-effector serves as the critical component responsible for executing specific operations. Its design characteristics directly influence key performance indicators, such as operational stability, fruit damage rates, and overall harvesting efficiency [61]. In fruit harvesting tasks, suction cups and multi-fingered grippers are commonly utilized to capture fruits and are typically actuated via pneumatic mechanisms. Cutting or twisting techniques are employed to separate the fruit from the stem [62]. For the harvesting of forest tree cones, the end-effector is usually designed as a harvesting head—a device combining clamping and vibratory functions. It employs hydraulic mechanisms to clamp onto the tree trunk and then utilizes a vibratory device to complete the harvesting process. Worth noting is that to mitigate the potential structural damage caused by vibrations, shock-absorbing devices are usually incorporated between the end-effector and the robotic arm.

In the realm of end-effector design, the agricultural and forestry sectors present unique requirements in terms of material selection and functional specifications. For robots geared toward harvesting tree cones in forests, the design tends to favor rigid materials like metals. These are often combined with components, such as rubber pads and shock-absorbing springs, to minimize potential damage to the tree structure. In contrast, the field of fruit-picking robots is undergoing a paradigm shift from rigid to flexible materials. With continued research, a variety of flexible materials like elastomers, granules, fabrics, fibers, and polymers are increasingly being incorporated into the design of end-effectors. Leveraging their diverse response characteristics, these flexible materials enable the construction of soft robotic hands with high compliance, adaptability, and stability, thus addressing the shortcomings of rigid mechanical hands, such as heavy weight, poor flexibility, and the propensity to damage the fruit. With advancements in 3D printing technology and new material science, some researchers are also employing biomimetic frameworks to design bio-inspired robotic hands. For instance, Pi J et al. [63] drew inspiration from the variable stiffness, infinite degrees of freedom, and high agility demonstrated by octopus tentacles during predation. They designed a three-fingered, flexible, bio-inspired mechanical hand for apple picking. Compared to other soft robotic hands, this design exhibited advantages, such as lower mass, excellent cushioning performance, and robust gripping capabilities.

To ensure the reasonableness of the picking action and structural design of the manipulator, researchers performed analog simulation and analysis using software, such as ADMAS, Robo DK (Robotic Design Kit), MATLAB, and other software, as well as intelligent algorithms, such as ant colony and neural network [64,65]. Therefore, the flexible robot has a wide range of potential applications. In the future, the manipulator will advance in the direction of greater flexibility and adaptability, which is also the predominant direction of current academic research. Zhang et al. [66] designed a three-finger flexible manipulator and constructed a clamping force pressure adjustment system to realize the non-destructive picking of cherries. Guo et al. [67] proposed a flexible underdriven manipulator for tomato picking based on the principle of FRE (Feature Rich Embedding) structural bionics, and the experiments showed that can pick and transport tomatoes of 65–95 mm without damage, with an effective gripping rate of 100% and strong stability.

4.3. Research on Travel Path Planning Technology

Tracked, wheeled, and humanoid structures are three typical walking mechanisms for picking robots. To increase the robot's work efficiency and autonomous navigation capability, researchers must investigate path-planning techniques under various structural forms. Path planning technology is a prerequisite for autonomous navigation, which seeks to optimize the robot's walking path and avoid behaviors, such as repeated missed operations and the robot's turning paths, in order to increase operational efficiency [68–70].

Path planning is subdivided into global path planning and local path planning based on the degree to which information about the surrounding environment is unavailable [71]. Classic algorithms include the grid method, A* algorithm, and Dijkstra algorithm, among others. Nonetheless, it requires precise information about the environment in advance, and its planning accuracy is poor when confronting unknown obstacles. Local path planning, on the other hand, focuses on generating a feasible path from the current position to the endpoint based on the current local environment and position information, with dynamic obstacle avoidance to ensure driving safety, and the classic algorithms include the dynamic window method, the local optimization method, and others. However, due to a lack of global environment data, the intended route may not be optimal on a global scale. Due to the complexity of the actual picking environment, there are limitations to the aforementioned classical algorithms, such as the grid method, whose performance is closely related to the grid size. A smaller grid size can achieve greater planning accuracy, but it will slow down the path decision-making speed, thereby affecting real-time. While a larger dimension can speed up the decision-making process, it will also reduce its precision. When there is a large number of obstacles, the dynamic window method will encounter issues, such as an inability to reconcile speed and safety [72]. Consequently, these constraints have already affected the robot's efficiency and safety [73].

In order to overcome the limitations of conventional algorithms, researchers began employing artificial intelligence techniques, such as reinforcement learning and deep learning, combined with RRT [74], ant colony [75], neural networks, and other improved intelligent algorithms, in order to optimize the original path planning function. When encountering dynamic and static obstacles, such as fruit trees, pedestrians, and operating machinery, it is able to plan obstacle avoidance paths in real time to ensure the safety of humans and machines and increase operating efficiency. Song et al. [76] proposed the MS-DDQN algorithm, which combines the multi-step update method with a two-depth Q-network and reinforcement learning techniques to enhance the robot's ability to sense distance. Wang et al. [77] proposed a deep reinforcement learning-based coverage path planning method for kiwifruit picking robots that combines the improved deep reinforcement learning algorithm Re-DQN with a LIDAR to effectively shorten the coverage path of kiwifruit orchards and enhance the navigation efficiency of kiwifruit picking robots.

Some researchers have also investigated the technology of multi-machine synergy, area division, and path replanning on the basis of single-robot operation so that the robot can complete the picking operation more intelligently and efficiently. This is also one of the primary areas of study for contemporary scholars. Cao et al. [78] implemented the global path planning and local dynamic obstacle avoidance function based on the study of improved A* algorithm and Bezier curve for multi-machine collaboration and combined the MATLAB platform to conduct simulation experiments, which for the first time satisfied the real-time and smoothness requirements of collaborative operations. Bae et al. [79] proposed a multi-robot path planning algorithm employing a combination of Deep q learning and convolutional neural network, which optimizes the multi-path planning strategy by learning the mutual influence law between each robot and makes the collaboration between robots more flexible and effective.

In recent years, with the rapid advancements in Unmanned Aerial Vehicle (UAV) technology, numerous academic studies have begun to explore the collaborative applications of UAVs and ground robots for synergistic aerial and terrestrial operations. UAVs, owing to their expansive field of view, can capture extensive ground-level information through aerial photography, thereby optimizing the environmental model construction for ground robots. Utilizing high-quality map data provided by UAVs, ground robots are able to plan their movement paths more accurately, effectively evade obstacles, and enhance the efficiency of harvesting tasks. Liu et al. [80] proposed an algorithm for collaborative localization and map fusion between aerial UAVs and ground robots under orthogonal aerial perspectives. This method successfully addressed the limitations of viewpoints in Simultaneous Localization and Mapping (SLAM) within complex scenarios. Wang et al. [81] introduced a visual SLAM technique for aerial mapping by UAVs. This innovation significantly improved the quality of mapping while also augmenting the mapping and navigation capabilities of ground robots in unknown environments.

4.4. Research on Visual Recognition Technology

Visual recognition technology holds an indispensable role in agricultural and forestry automation equipment, especially in agricultural and forestry robots. In the context of pruning robots, this technology can accurately identify overgrown or damaged twigs and relies on industrial control systems to locate the spatial coordinates of the target branches. Based on this data, algorithms further plan the movement trajectory of the mechanical arm, which is ultimately executed by the end-effector for precise trimming, achieving intelligent pruning operations. In the application of plant protection robots, visual recognition technology uses cameras or sensors to detect the health and pest conditions of plants. By analyzing captured images or collected sensor data, algorithms can assess the health of the plants. Once a diagnosis confirms that the plants are affected by pests or diseases, the plant protection robot can automatically execute pesticide spraying tasks. It targets the affected areas, thereby minimizing pesticide waste and environmental pollution to the greatest extent.

For agricultural and forestry harvesting robots, visual recognition technology is primarily used for the accurate identification of fruits or tree trunks, a step that plays a crucial role in the entire harvesting process. The speed and accuracy of identification directly impact the robot's harvesting efficiency [82]. Focusing on the two major types of harvesting objects, fruits and coniferous cones, visual recognition faces different sets of challenges and complexities. Coniferous cones usually grow in areas with complex environments and tall trees, and the fruits are often obscured by branches and leaves, undoubtedly increasing the difficulty of visual recognition. Additionally, due to the hard skin of these fruits, robots often shake the tree trunks or branches to improve harvesting efficiency in some standardized planting areas. Conversely, in fruit-picking robots targeting tomatoes and strawberries, the focus of visual recognition is mainly centered on the fruits themselves.

Primarily, methods for selecting targets include feature-based target recognition and deep learning [83]. The feature-based method recognizes fruits based on their color, shape, and other characteristics [84,85]. However, in the actual harvesting operations of agricultural and forestry products, especially for fresh fruits, there exists a series of complex factors that complicate visual recognition. These factors include the overlapping and obscuring of fruits, as well as their high color similarity to background leaves. In forest environments, the tree trunk identification process can also be disturbed by uneven lighting and shadows. These complexities significantly impact the efficiency of feature-based recognition methods, resulting in slower recognition speeds, reduced accuracy, and weakened real-time performance of the system. Therefore, these limitations, to a certain extent, constrain the applicability and feasibility of such recognition technologies in broader application scenarios [86,87].

In contrast, the deep learning method is to construct a deep convolutional neural network to refine the bottom layer features of the picking target image. Through continuous iteration, it can form a deep learning model with high-level features, which can autonomously learn and optimize the network parameters through the Back Propagation algorithm (BP) so as to continuously improve the recognition accuracy and realize the autonomous learning of features and automation [88–90]. Current deep convolutional neural networks in the field of target recognition include You Only Look Once (YOLO), Single Shot Multi Box Detector (SSD), Faster R-CNN, Retina Net, etc. Deep learning techniques feature multi-level representations and robust learning capabilities [91,92]. In scenes with complex visual information, such as fruit overlapping and occlusion, the recognition ability of deep learning methods performs exceptionally well and has consequently attracted considerable interest. Liu et al. [93] proposed an innovative method for detecting the trunks of oil-tea trees based on optimized improvements to the YOLOv7 network. During the experimental evaluation, this enhanced model was rigorously compared with YOLOv3, YOLOv4, YOLOv5, and the original YOLOv7 network. The experimental results revealed that the optimized model demonstrated significantly superior performance in terms of both detection accuracy and speed compared to the other reference network models. Fu et al. [94] used the YOLOv4 algorithm to achieve rapid and accurate recognition of unripe banana bunches and stalks in various lighting and leaf shading scenarios.

5. Conclusions

The purpose of this paper is to examine the current research status and future direction of agroforestry robot harvesting in China. In order to accomplish this, we cited a large number of publications and visualized a total of 1271 bibliographic records from the WoS core and CNKI databases using the scientometric analysis tool Cite Space. This scientometric study provides a comprehensive and accurate depiction of the field's knowledge structure and trends. In addition, by combining the visualization results and comparing the common issues between domestic and international studies in this field, we predict the future development trajectory of this field in order to provide scholars with insight into the future research emphasis of this field.

After analyzing the results, we came to the following conclusion: In the mid-1990s, Chinese scholars began to pay attention to the research on agroforestry harvesting robots, which deepened gradually after 2012. Not only did the number of annual publications increase significantly, but so did the proportion of Chinese authors who published English literature. China has become the country with the most publications in this field of study, but an analysis of Chinese literature reveals that cooperation and interchange between domestic institutions are insufficient, and large research teams have not yet been formed. In the English literature, two teams led by SCAU and NWAFU have been established, but their influence in the international arena is inferior to that of institutions, such as AIST, UT, and MIT, so Chinese research institutions must strengthen their cooperation with foreign institutions.

Through keyword co-occurrence and cluster analysis, it is evident that the hottest research directions in the field of agriculture and forestry picking robots are primarily concentrated on four aspects: picking target recognition, motion planning and control, structural design simulation, and walking path planning.

Based on the aforementioned research findings and keyword co-occurrence analysis, this study predicts four future development directions for this field. To ensure the picking performance and realize the fine control of the picking object, research on the motion planning and control of the picking robot manipulator should be intensified, while the structural design and simulation analysis of the manipulator can provide more potential solutions for the future development of the field, combining the most advanced artificial intelligence technology to realize the robot's autonomous navigation, automatic obstacle avoidance, and self-adaptive behavior.

Comparing Chinese and English literature, this paper provides a mapped knowledge analysis of the research history, current status, and prospective development trends in the field of agroforestry picking robots in China based on theoretical analysis and research. This provides a useful reference for those involved in the field and helps them comprehend the current research status and future direction of the field's development. Note that the samples used in this investigation are limited to English and Chinese literature from the WoS Core Collection and CNKI databases, respectively. In order to enhance the precision of the knowledge structure in the field of agroforestry harvesting robotics research, it will be necessary to diversify the data sources in the future. In addition, we should encourage the use of additional visualization techniques in order to enrich the map of this knowledge domain.

Author Contributions: Conceptualization, N.J. and H.Z.; methodology, N.J. and H.Z.; software, N.J. and H.Z.; investigation, N.J., H.Z. and H.G.; resources, N.J. and J.L.; data curation, N.J., H.Z. and H.G.; writing—original draft preparation, N.J., H.Z. and H.G.; writing—review and editing, N.J. and H.Z.; funding acquisition, N.J. and J.L. All authors have read and agreed to the published version of the manuscripts.

Funding: This research was funded by the national key research and development project "Research and development of technology and equipment for harvesting walnut and wolfberry". (2022YFD2202105-1).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Acknowledgments: All authors have consented to the publication of this article and thank the editors and anonymous reviewers for their valuable suggestions on this article.

Conflicts of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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