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Technology Recommendations for an Innovative Agricultural Robot Design Based on Technology Knowledge Graphs

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Abstract: The process of agricultural robot design is a complex system requiring the cooperation and integration of agricultural, machinery, automation, and information technology. These demands create great challenges for the innovative design of agricultural robots. Meanwhile, more than 95% of the latest inventions and creations in the world are recorded in the patent literature. In order to make effective use of the information and data resources of patents, shorten the design cycle, and provide knowledge for the designers, according to the operation's objectives, an agricultural robot technology knowledge graph (TKG) was established for innovative designs. By analyzing the patent information, a patent IPC co-classification network (IPCNet) for adaptive design process recognition was put forward to meet the requirements of the different operation objectives and operation links. Through the extraction of the technology keywords and efficacy keywords, based on the word co-occurrence network (WCONet), a technology–efficacy map (TEM) was constructed. Through the integration of the adaptive design process and the TEM, the agricultural robot design TKG was constructed for determining technological recommendations for agricultural robot design. The case of the citrus picking robot design was realized to implement the design process. With the technology recommendation results, the moving system, body, and end-effector for the citrus picking robot were designed to verify the results of the recommendation.

Keywords: knowledge graph; agricultural robot; technology recommendation; innovative design

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1. Introduction

In response to the requirements of smart agriculture and intelligent agricultural equipment, robotic technologies in agriculture are developing rapidly. Compared with traditional agricultural machinery, agricultural robots have the characteristics of complex structures and functions, comprehensive electromechanical control, and a complex industrial chain [1]. This creates great challenges to R&D for agricultural robots. In the past 30 years, the agricultural robots that have been developed [2–4] include the complete systems [5–7] or the subsystem of a mechanical system (i.e., the manipulator [8–10] and the end-effector [11,12], guidance and navigation [13,14], and target recognition and localization [15–18] et al. The design process for the agricultural robot is the determination of the degrees of freedom (DOF), the numbers of arms, and the workspace [19], and the system design includes the traveling platform, sensors, manipulations, end-effector, and the control system [2,3,20].

The working environment of agricultural robots is changeable and unstructured. Therefore, the process of agricultural robot design needs to meet the agronomic demands of the agricultural operation scene and the operation objective (i.e., the variation of objects for fruit picking includes the position, size, shape, and reflectance, and the variation of the sense includes the orchard, greenhouse, indoor, and open field [19]), as well as the cooperation and integration of machinery, automation, and information technology. Those demands created great challenges for the designers of innovative agricultural robot designs. Designers not only need to understand the relevant technologies, such as robot-related mechanical systems, automatic control, sensors, and information processing, but also need to understand the knowledge relevant to the agricultural robot operation scene and the operation's objectives [21,22].

Traditionally, the process of mechanical system design has mainly relied on experience and knowledge. In order to improve the design efficiency, various methodologies have been developed to aid design, such as knowledge reuse [23,24], TRIZ (theory of inventive problem solving) [25–29], and infused design [30], to realize the use of knowledge from the different domains. The reuse of design knowledge in a specific domain is a research hotspot in the field of product design [23,31,32]. Modern product design needs knowledge reorganization, transfer, and transformation in multi-disciplinary fields, such as machinery, information, automation, and biology. More than 95% of the latest inventions and creations in the world are recorded by the patent literature. In order to utilize the knowledge of the patents, Trappey (2013) developed a novel knowledge management approach using an ontology-based artificial neural network (ANN) algorithm to automatically classify and search for the knowledge found in documents stored in huge online patent corpora [33]. An intelligent recommendation system was developed to enable timely and effective patent searches prior to, during, and after design collaboration in order to prevent the potential infringement of existing intellectual property rights (IPR) and to secure new IPR for market advantages [34]. By combining the technological terms identified, the potential technological topics captured, and the distribution and evolution patterns of the technological topics analyzed in patents, the technical topics and the future R&D hotspots in 3D printing were identified [35].

Knowledge graphs (KG) are a methodology using mathematics, graphics and information processing, and information visualization theory and methods, combined with bibliometric citation analysis and co-occurrence analysis, to show the core technology, development history, frontier fields, and overall knowledge structure of a research field. Thus, by using topic analysis, relation rule mining, and NLP (natural language processing) to extract the knowledge to the patent, the TKG was established. Brügmann (2015) developed an operational prototype of a workbench for intelligent patent document analysis and summarization that has five modules for the individual aspects of patent analysis (entity recognition, lexical chain identification, invention composition derivation, segmentation, and claim–description alignment) and a module for patent summarization [36]. Trappey (2020) developed a hierarchical Latent Dirichlet Allocation (LDA)-based approach to discover topics and form a top-down ontology, namely a semantic schema, representing the collective patent knowledge [37]. By applying the natural language process (NLP) and patent mining, Ye (2021) provided a domain knowledge graph automatic building method, and an approach to cross-domain knowledge discovery was established to assist with the conceptual stage of the design process related to mechanical engineering [38] in order to overcome the shortages in the query-driven patent search contexts by defining and constructing a patent knowledge graph.

The technology knowledge graph (TKG) can provide the domain knowledge at the level of terms (words or phrases) for agricultural robot design [39]. Hurtado (2015) presented an approach that automatically translated the hierarchies found in the patent classification codes into concept hierarchies based on reclassification techniques and the relationships between different application domains. This approach could realize the automatic inference of implicit knowledge [40]. Deng (2021) defined and constructed a patent knowledge graph to capture the semantic information between keywords in the patent domain. By comparing the weighted graphs based on the graph edit distance measure, a recommended patent approach was proposed to companies [41]. Liu (2020) provided a patent knowledge query tool based on function, in which, by using a semi-supervised learning algorithm, function information was automatically classified and labeled by the functional basis. The retrieved cross-domain patents could be purposefully recommended to trigger designers' creativity [42].

In order to meet the agronomic demands of the operation scene, the operation objective, and the operation link for the agricultural robot, and to make effective use of the information of patents, shorten the design cycle, and provide knowledge for the designers, the domain patents were collected to realize the path recognition and technology–efficacy map construction for the robot design process, and the technology knowledge graph (TKG) was established to realize the technology recommendation process for the innovative agricultural robot design. In addition, a case study of a citrus picking robot design was implemented to describe the process of innovative agricultural robot design.

2. Materials and Methods

2.1. Data Sources

Considering the technical background, the key technical points, and the technical developments of the patents with the analyzed results for the agricultural robot patents [43] about the keywords, the International Patent Classification (IPC), and the Derwent Manual Code (MC), the query set was developed, as shown in Table 1. The patents from the Derwent Innovations Index (DII) database in the WEB of Science (WoS) database were searched. In total, 9042 patents related to agricultural robots were obtained.

Table 1. Agricultural robot patent query set, where TS is the topic terms in the Title and Abstract fields within a patent record, MAN is the Derwent Manual Code(s) field within a patent record, and the IP is the International Patent Classification (IPC) field within a patent record, * is the wildcard.

Query Set	Search Results
((TS = (agriculture * or crop or crops or fruit or fruits or vegetable * or harvest * or seedling *) or MAN = (X25-N * or X22-X11 or X22-P09 or Q19-G or T06-D01 * or A12-W04 * or X25-X02 *) or IP = (A01B* or A01C * or A01D * or A01F * or A01G * or A01M-021 *)) AND (TS = (robot * or manipulator * or "mechanical arm" or "mechanical arms" or "mechanical hand" or "mechanical hands") or IP = (B25J *) or MAN = (X25-A03E * or T06-D07B * or V03-U14 * or V04-M30R * or V04-Q30R * or V06-U05 * or V04-R04F1 * or X27-U * or S05-B07 *))) not (IP = (A01G-005 * or A01G-023 *) or MAN = (X25-N02 * or T06-D01C))	9402

2.2. Adaptive Design Process of Agricultural Robots Based on IPC Co-Classification Networks

Agricultural robots have different requirements regarding the operation objectives and operation links. For example, a picking robot needs different end-effectors for its operation objectives: the design of the body of the robot needs to consider the agronomic requirements, and the moving mechanism needs to consider the topographic conditions; however, for a mowing robot, the main considerations are the design and control of the moving mechanism. Therefore, to realize the path selection of agricultural robot design based on IPC co-occurrence network analysis, an adaptive design process for agricultural robots with different operation objectives and operation links is needed.

2.2.1. IPC Co-Classification Network (IPCNet)

The International Patent Classification (IPC) was established by the Strasbourg Agreement in 1971 [44]. The IPC provides a hierarchical system of language-independent symbols for the classification of patents and utility models according to the different areas of technology to which they pertain [45]. Thus, each patent has an IPC classification. When a patent applies to two technology classifications simultaneously, it has the corresponding IPC classifications, which produce a link due to such IPC classifications. When the number of patent applications and classifications is sufficient, a patent IPC co-class network (IPCNet) is formed [46]. Patent co-classification is a suitable approach used in patent bibliographical studies for analyzing technology flows, trends [47], evolution [48], and development directions [49].

2.2.2. Path Recognition of IPCNet

When a new design demand is put forward for a certain operation objective, the IPC classification for the operation objective or operation link will be determined. Thus, an agricultural robot design process needs to be constructed. IPCNet can be used for technology flows. According to this consideration, the SPLC (search path link code) was used to identify the main path of the IPCNet. The IPC of the operation objective was defined as the starting IPC; the ending IPC refers to the IPC with only one connection with another IPC. After calculation of the sum of the occurrences of each edge in all paths of the starting IPC and the ending IPC, the largest path for SPLC is the main path [50].

2.3. Agricultural Robot Technology Knowledge Graph Based on Patents

The TKG comprises the domain technology at the levels of terms (words or phrases). To establish the domain TKG for agricultural robot design, patents and domain knowledge were collected.

2.3.1. Patent TKG

A patent document includes an application and its published information, such as the application ID, the inventor, the applicant, the title, the content, and claims. The information can be retrieved from the DII database. Figure 1 shows the entity-relationship description of the patent knowledge graph.

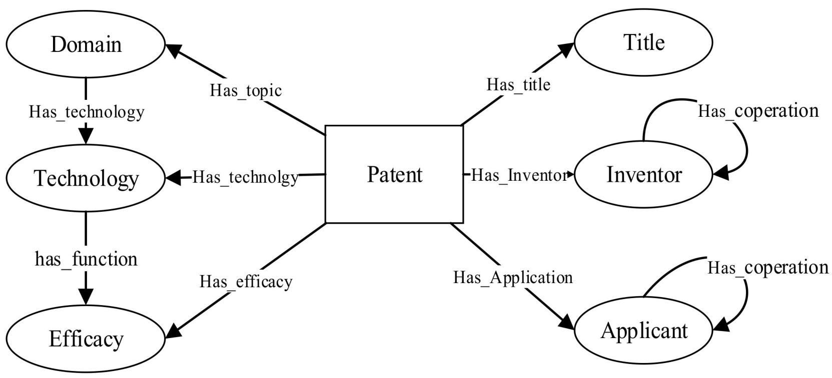


Figure 1. Patent TKG.

2.3.2. Robot Component TKG

According to the technical characteristics of agricultural robots, a robot mainly includes mechanical system, sensing system, and control system, and the mechanical system includes a moving system, a body, an end-effector, a navigation and control system, and a target detection and recognition system. The robot component TKG is shown in Figure 2.

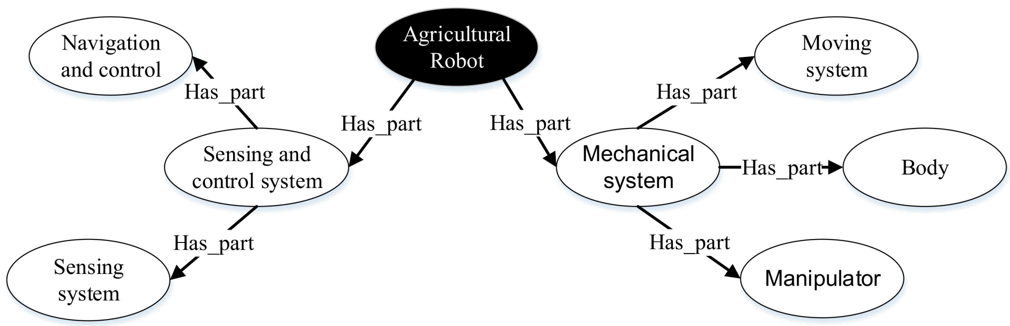


Figure 2. Robot component TKG.

2.4. Domain Technology–Efficacy Map Based on TKG

2.4.1. Construction Process of the Technology–Efficacy Map Based on the TKG

According to the characteristics of the patent, the construction process of a technical efficacy map includes knowledge extraction and construction of a technology–efficacy map (TEM), shown in Figure 3. Knowledge extraction includes acquisition, domain term analysis, and entity-relationship extraction. By extracting the knowledge from the patent, the domain TKG and knowledge base (KB) can be established. With the TKG and KB, the domain's technical words library and efficacy words library can be built. Through matching the technical words and efficacy words of the patent, a TEM can be established.

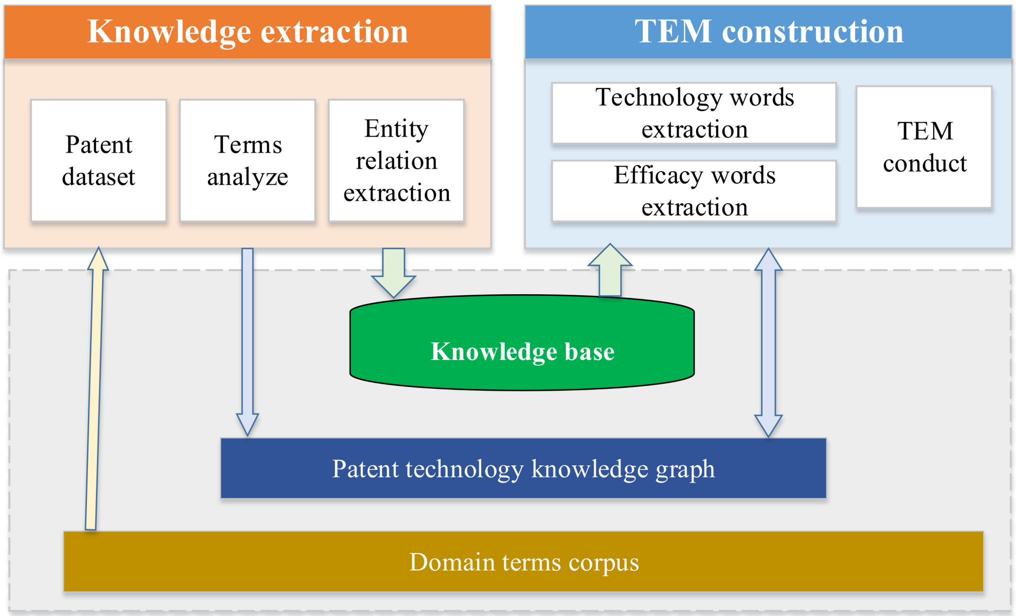


Figure 3. Construction process of the technical efficacy map based on the patent TKG.

2.4.2. Technical Word Library

The domain term corpus has been established for NLP, such as Wikipedia, Project Gutenberg, etc. In order to establish the agricultural knowledge graph, AgriKG was established to automatically recognize agricultural entities from unstructured text and link them to form a knowledge graph [51]. However, there is no library for agricultural robots. With the unstructured text of agricultural robot patents, the TF-IDF (term frequency–inverse document frequency) model was used to extract the words from the patent document [52]. According to the robot components, TKG classified the patents as first-level technology. Through a combination of expert interviews, patent analysis, and manual tagging, the technology terms were constructed for the domain of agricultural robots. The construction process of the agricultural robot KG is shown in Figure 4.

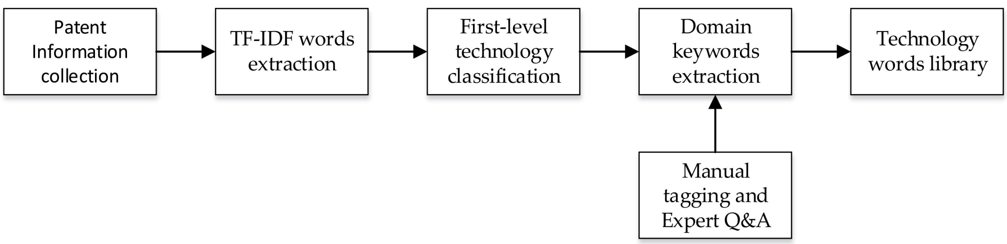


Figure 4. Construction process of the domain's technical word library.

2.4.3. Efficacy Word Library

In the field of intelligence and information research, efficacy words mainly focus on the advantages of using the technology, such as reducing the cost and improving the efficiency. These efficacy words can only be defined as first-level effects in the design process. In the design of agricultural robots, in order to obtain data on the efficacy of the technology, we needed to obtain details of the efficacy of the robots, such as reduced damage, obstacle overpass, etc. In this research, we established the efficacy word library by using the WCONet of the technology. The process of constructing the efficacy words library is shown in Figure 5. From the results of the word extraction based on TF-IDF, using the WCONet technology combined with expert interviews, patent analysis, and manual tagging, the efficacy word library was constructed.

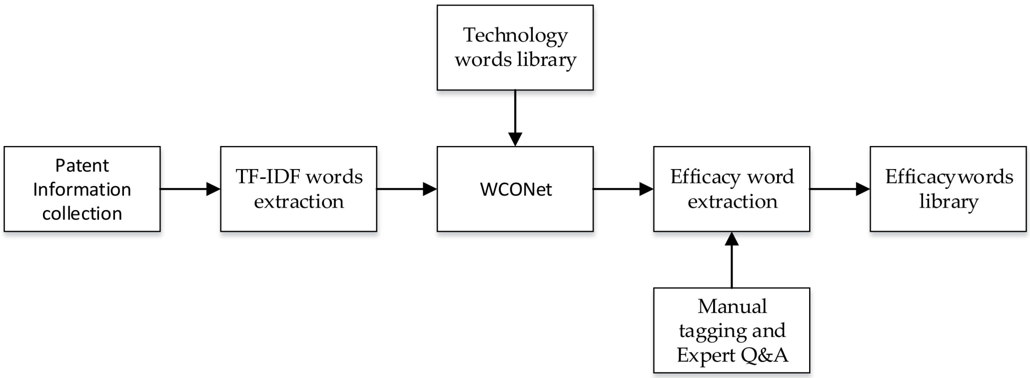


Figure 5. Construction process of the domain's efficacy words.

2.5. Agricultural Robot Design TKG

According to the key technologies identified for agricultural robots, the field of agricultural robots needs to consider the integration of agricultural machinery and agronomy, as well as the operation objectives, the operation scene, and the operation links. Thus, the words need to be classified as relating to the operation objectives, the operation sense, and the operation link of the agricultural robot according to each functional link of the robot, in combination with the opinions of experts in the field of agricultural robots. For operation scenarios, technologies, functions, and other categories, the generation module constructs the same or a different co-occurrence word matrix. The agricultural robot design TKG is shown in Figure 6. This TKG includes:

- Technology–operation objective and technology–operation scene (link) relationships to identify technology for matching the demands of the operation objective and the operation scene (link);
- Efficacy–operation objective and efficacy–operation scene (link) relationships to describe the key problems (efficacy) to be solved for the operation objective, operation scene, and operation links;
- Technology–efficacy relationships to describe how the problem (efficacy) can be solved with the technology;
- Technology–technology combination relationships to describe when the technology has been improved and which technologies need to be improved accordingly, and to find the potential technology chains and how improving them can achieve efficacy (e.g., reduced costs or improved efficiency).

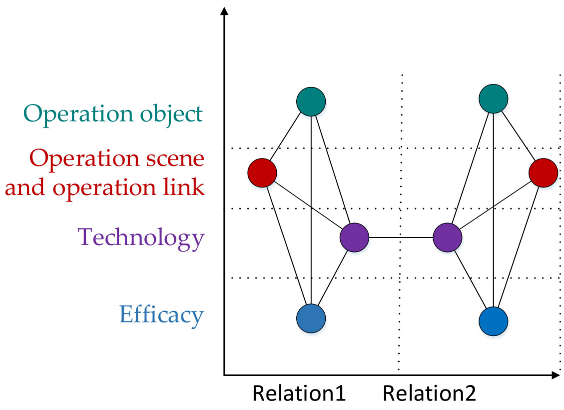


Figure 6. The agricultural robot design TKG.

2.6. *Technology Recommendation Process for an Agricultural Robot Design Based on TKG*

Figure 7 shows the technology recommendation process for an innovative agricultural robot design based on TKG. When the design task was determined, with the KB for operation objective, operation scene, and operation links, the efficacy words for the design demands could be obtained through the technology–efficacy map. Matching between the efficacy and the technology can be implemented to obtain the technology, and the corresponding patent can be obtained from the patent TKG.

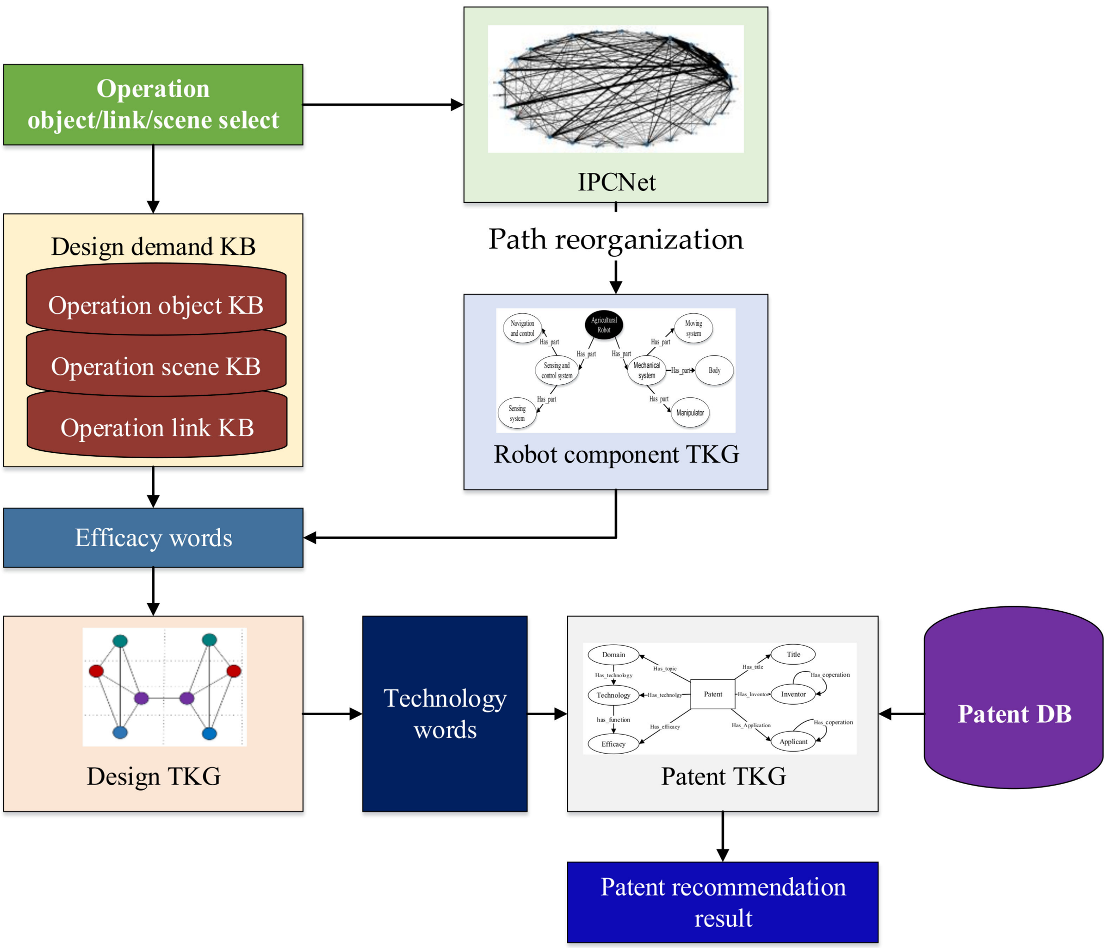


Figure 7. Technology recommendation process for agricultural robot design based on a technology efficacy diagram.

3. Results

3.1. Adaptive Design Process for an Agricultural Robot Based on IPCNet

3.1.1. Patent IPCNet of the Agricultural Robot Domain

The results of the query regarding agricultural robots revealed 6632 IPC classifications. Figure 8 shows the IPCNet for the agricultural robot patents, along with the occurrence (frequency) of more than 50 IPC nodes. The top IPCs were mainly distributed in the fields of A01C (planting, sowing, and fertilizing), A01D (harvesting and mowing), B25J (manipulators, and chambers provided with manipulation devices), G05D (systems for controlling or regulating non-electric variables), A01G (horticulture; cultivation of vegetables, flowers, rice, fruit, vines, hops, or seaweed; forestry; or watering). The results show that the agricultural robot technologies are mainly about the manipulators and their controlling or regulating systems for agricultural production (planting, sowing, fertilizing, spraying, harvesting, and mowing, etc.).

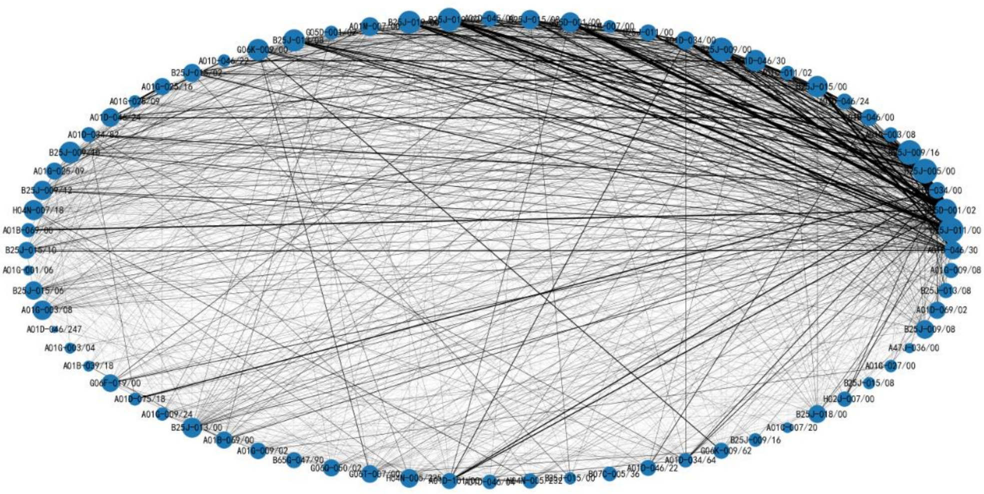


Figure 8. IPC co-classification network (IPCNet) of the agricultural robot patents.

3.1.2. Path Recognition of the Design Process

Table 2 shows the nodes with a connection frequency of more than 50 in the IPCNet. Thus, the technology domains involved in agricultural robots include the integration of agricultural production (A01), manipulators (B25), and controlling and regulation systems (G05); in other words, the technological developments of agricultural robots include the integration of agricultural machinery and agronomy, and the integration of electromechanical control. The technology flow is from different operation objectives (such as horticultural crops, vegetables, fruits and vegetables, and flower cultivation (A01G)) and operation processes (such as planting, sowing, and fertilization (A01C); harvesting or picking (A01D-046/30); mowing (A01D-034/00); mobile irrigation (A01G-025/09)) through to the mobile manipulator (B25J-005/00), the end effector (B25J-015/00), its controller (B25J-011/00), the sensing device (B25J-019/02), the program control method (B25J-009/16), the position control (G05D-001/00), and the automatic moving control (G05D-001/02) of the robots' operation process.

From the node connections of the IPCNet, based on the SPLC algorithm, the results regarding path recognition for the agricultural robot are shown in Figure 9. For agricultural robots with different operation objectives or operation links, the path is different. For robotic picking devices (A01D-046/30), the end-effector (B25J-015/00) is the key technology, and the technology domains include the moving system (manipulators mounted on wheels or on carriages (B25J-005/00) and the position control (G05D-001/02)), manipulators (B25J-011/00), sensing devices (B25J-019/02), and control or regulating systems (B25J-019/16). For mowing robots (A01D-034/00), the technology domains only include the moving system (B25J-005/00) and position control (G05D-001/02). Therefore, the agricultural robot design process needs to combine the operation objectives and operation links to adaptively establish a design process based on the IPCNet analysis.

Table 2. The nodes with a connection frequency of more than 50 in the IPCNet.

ID	IPC 1	IPC2	Connection Frequency
1	A01D-034/00	G05D-001/00	50
2	A01D-034/00	G05D-001/02	260
3	A01D-046/30	B25J-015/00	54
4	A01G-025/09	A01G-025/16	52
5	B25J-005/00	B25J-009/16	74
6	B25J-005/00	B25J-011/00	114
7	B25J-005/00	G05D-001/02	56
8	B25J-009/00	B25J-009/16	51
9	B25J-009/16	B25J-019/02	64
10	B25J-011/00	A01D-046/30	80
11	B25J-011/00	B25J-009/16	134
12	B25J-011/00	B25J-015/00	53
13	B25J-011/00	B25J-019/00	50
14	B25J-011/00	B25J-019/02	72
15	G05D-001/02	G05D-001/00	105

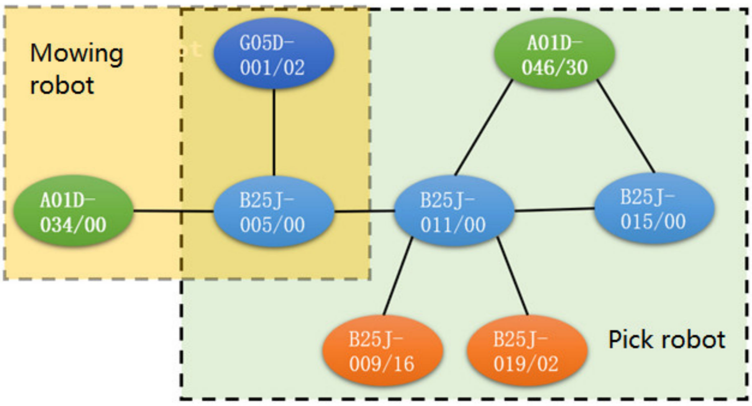


Figure 9. Key technology path recognition results based on IPCNet analysis.

3.2. Agricultural Robot TEM Based on WCONet

3.2.1. Agricultural Robot TEM

Figure 10 shows the keywords of recognition, detection, and location in the agricultural robot. According to the results of the extraction and the cluster analysis, the terms and their distributions in the field of recognition, detection, and location in agricultural robots are shown in Figure 10. The results show that the terms for the recognition, detection, and location of agricultural robots involve the recognition, detection, and location of the operation objectives (fruits, vegetables, apples, orange, tea, strawberries), operation links (weeding, spraying, irrigation, sowing, picking, harvesting), and the operation scenes (greenhouse, orchard). The adopted technologies include images (image, vision), video, laser, and RFID tags to realize the recognition, location, navigation, and obstacle avoidance of agricultural robots' operation objectives.

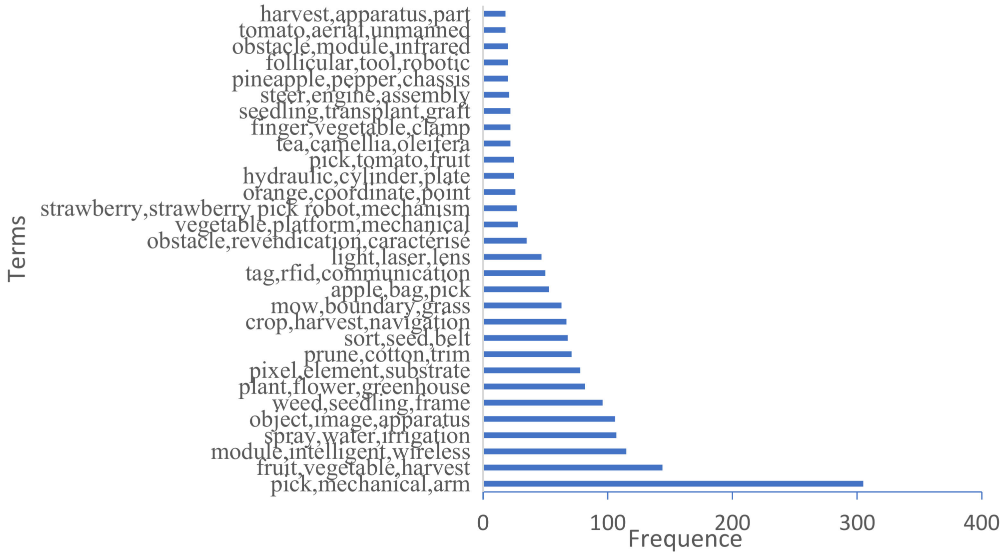


Figure 10. Keywords of recognition, detection, and location of agricultural robots.

3.2.2. Design TKG Based on WCONet

Figure 11 shows the keyword co-occurrence matrix of vision positioning technology in fruit picking robots. The operation objective is fruit; the operation link is picking/harvesting; the technology words are "image", "vision", and "laser"; and the efficacy words are "target detection" and "position". It can be seen from the figure that image and vision technologies have more advantages than the laser scanning method in the fruit target recognition and positioning of the picking robot. From the frequency of co-occurrence words, there is relatively more work on detection and positioning based on vision and laser. Based on the WCONet analysis, the terms for the agricultural robot design TKG are shown in Table 3.

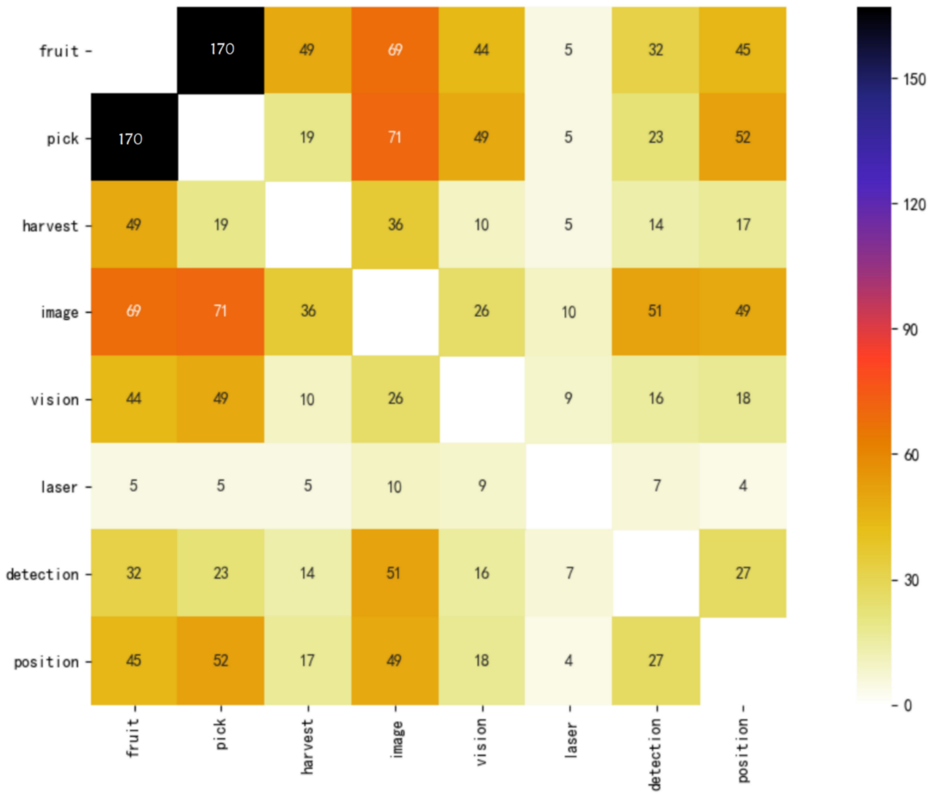


Figure 11. Keyword co-occurrence matrix of position for a fruit harvesting robot.

Table 3. Terms for the agricultural robot design TKG.

TKG Node	Terms
Operation objective	Apple, orange, tea, strawberry . . .
Operation sense	Greenhouse, orchard, indoor, open field . . .
Operation link	Weed, spray, harvest . . .
Technology	Image, vision, video, laser, RFID, tag . . .
Efficacy	Location, navigation, and obstacle avoidance . . .

4. Case Study of a Citrus Picking Robot

4.1. The Design Demands of the Citrus Picking Robot

In order to pick citrus, according to the citrus growth conditions and the characteristics of the citrus tree, and due to the fact that the patents are mainly referred on the system and structure innovation, especially in the agricultural robot patents, the design of the citrus picking robot is mainly focused on the mechanical system, i.e., the moving system, the body and arm, and the end-effector, etc. The key problems to be solved for each functional component of the citrus picking robot and the efficacy words are shown in Table 4. Citrus is mainly grown on sloping terrain in hilly and mountainous areas, and the ground often has obstacles. Thus, for the moving system, the designer needs to realize movement in these conditions. According to the IPC classification, the citrus is the fruit, so the starting IPC of the IPCNet for the citrus picking robot is A01D-046/30. The citrus picking robot design process is presented in Figure 9.

Table 4. Key problems to be solved for each functional component of the citrus picking robot and the corresponding efficacy words.

Functional Component of the Robot	The Problem Needing to Be Solved	Efficacy Word
Moving system	Moving on the sloping terrain of hilly and mountainous areas and overpassing obstacles	Hilly and mountainous, slope terrain, obstacle overpass
Body	Vertical large-scale canopy operation of citrus trees	Vertical, large-scale
End-effector	Prevent clamping damage to fruits	Spherical, clamping damage

4.2. Technology Recommendations for the Moving System and the Body of the Picking Robot

According to the efficacy words for the citrus picking robot design, based on the TKG of the agricultural robot, the technology recommendation results are shown in Table 5. The moving systems for the sloping terrain of hilly and mountainous areas include wheels, crawlers, and fixed track systems. The fixed track system is mainly used for picking under specific structural conditions. In the recommendations for the robot body, the main structure is the multi-joint manipulator. Mainly, picking robots that operate on hills and slopes adopt a crawler structure to pass over obstacles. Moreover, to meet the demands of the vertical large-scale canopy operations of citrus trees, the shear forklifting mechanism can be used to expand the working space of the manipulator in the vertical direction. Therefore, a combination of the crawler moving mechanism and the shear forklifting mechanism meets the demands of the citrus picking robot.

4.3. Technology Recommendations for End-Effector

Citrus fruits are typically spherical fruits, and the end-effector needs to avoid clamping damage to the fruit. Using “spherical fruit” and “clamp damage” as the efficacy words, and end-effector as the first-level technology, the technology recommendation results for the end-effector are shown in Table 6. The end-effector for circus fruit picking needs to both cut the stem and clamp the fruit. The stem cutting technologies include shearing, twisting, laser cutting, etc. Fruit clamping technologies include two fingers, multiple fingers, suckers, straws, tube swallowing, etc.

Table 5. Technical scheme of the moving system and the body of the citrus picking robot and related patents.

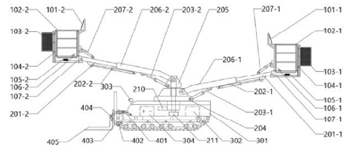
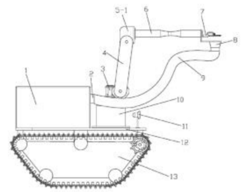
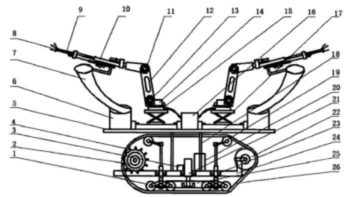
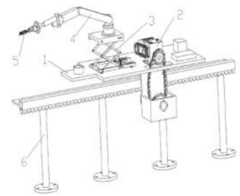
Technology Words	Efficacy Words	Title	Patent Number	Diagram
Crawler	Hilly	Mountain orchard double-cantilever telescopic picking machine, which has fork angle adjusting hydraulic cylinder connected with hydraulic station through fork angle adjusting electromagnetic valve, and fork lifting hydraulic cylinder connected with hydraulic station	CN212413887U	
	Hilly	Intelligent mandarin orange picking machine that has mandarin orange funnel that is connected with connecting port of mandarin orange collecting box through connecting hose, and base connecting plate that is fixed on top of loading platform	CN208724427U	
	Hilly	Apple picking robot, which has effector installed with camera, infrared position sensor, and apple picking pressure sensor, and picking machine arm connected to servo motor to drive picking machine arm picking pressure sensor, and picking machine arm connected to servo motor to drive picking machine arm	CN105746092A	
Fixed track system	Hilly	Orbital tea picking robot for use in hilly mountainous area, which has mechanical arm that is mounted on lifting device, and picking hand that is mounted on output end of mechanical arm	CN108555921A	

Table 5. *Cont.*

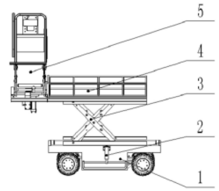
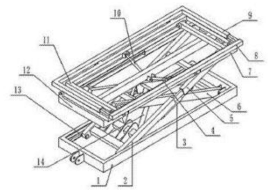
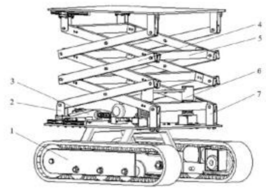
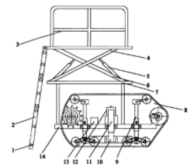
Technology Words	Efficacy Words	Title	Patent Number	Diagram
Wheels	Hilly	Picking device for hilly and mountainous areas, which has oil cylinder mounting support that is connected to fixed end of oil cylinder, where installation direction of oil cylinder is set perpendicular to ground	CN111201889-A	
	Hilly, vertical	Hill mountain orchard picking platform posture adjusting mechanism, which has left long side frame formed with square groove, and longitudinal adjusting hydraulic cylinder whose lower end is connected with vertical adjusting frame	CN207491561-U	
Shear forklifting	Large-scale	Horizontal driving elastic auxiliary starting device for scissors lifting platform, which has spring rod whose upper part is connected at inside of spring cap, where lower part of spring rod is connected to spring base through hole	CN106800254-B	
	Hilly, large-scale	Adjustable flat mountain orchard fruit picking platform that has inner arm and top end of outer arm that are fixedly connected with bottom end of telescopic ladder, and baffle arm that is mounted on enclosure	CN104067780A	

Table 5. *Cont.*

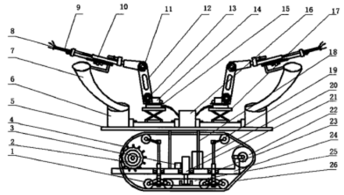
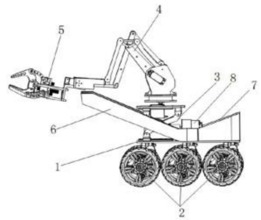
Technology Words	Efficacy Words	Title	Patent Number	Diagram
Arm	Large-scale	Apple picking robot, which has effector installed with camera, infrared position sensor, and apple picking pressure sensor, and picking machine arm connected to servo motor to drive picking machine arm picking pressure sensor, and picking machine arm connected to servo motor to drive picking machine arm	CN105746092-A	
	Large-scale	Vegetable and fruits picking robot for vegetable and fruit picking system, which has chassis fixed with camera that is electrically connected with main control circuit board, where end of slide way is connected with fruit storage basket	CN211931423-U	

Table 6. Grabbing and cutting modes for spherical fruits.

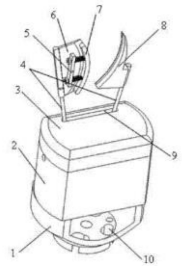
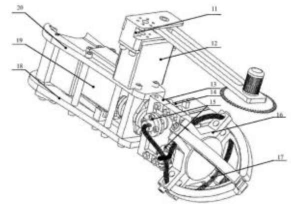
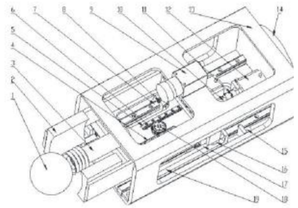
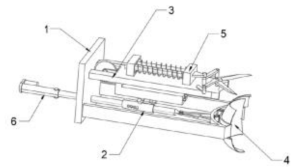
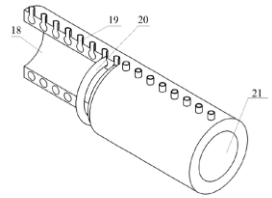
Technology Words	Efficacy Words	Title	Patent Number	Diagram
Two fingers	Clamp, shearing	Clamp shearing strength integrated meter picking robot end actuator that has double-screw bolt that is passed through fixing plate, and is screwed on left clamping surface	CN103004374A	

Table 6. *Cont.*

Technology Words	Efficacy Words	Title	Patent Number	Diagram
Multiple fingers	Spherical, clamp	Grab spherical fruit and vegetable picking robot end effector with integral cutting function, which has flexible shaft that passes through limit hole of base while two ends are, respectively, connected to driving servo motor	CN107041210-A	
Suckers	Spherical, clamp	Six-degree-of-freedom robot end effector for grasping spherical fruit, which has guide rail located in mounting shell, sliding block connected to clamping sucker driving plate through bolt, and another guide rail located above clamping sucker driving plate	CN213214398-U	
Suckers	Spherical, clamp	End effector of melon and fruit picking robot that has clamping mechanism that is installed at right end of electric push rod transmission mechanism and time delay mechanism whose left end is connected with upper portion of rear support plate	CN111937592-A	
Tube swallowing	Spherical, damage	Swallowing fruit and vegetable picking robot, which comprises an intelligent mobile platform, a bionic swallowing transport device, a robot body, and an industrial computer, while bionic swallowing transport device is installed through robot body	CN111972127A	

4.4. Design of the Citrus Picking Robot

With the technology recommendation results of the citrus picking robot, we designed the picking robot shown in Figure 12. The main structures of the system include the components described in the sections below.

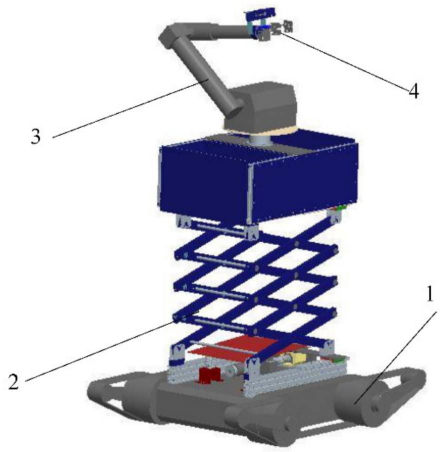


Figure 12. Citrus picking robot with a crawl moving system and a shear forklifting and arm manipulator: 1, crawler; 2, shear forklift; 3, 2-DOF arm manipulator; 4, end-effector.

4.4.1. Crawl Moving Mechanism

The JaugarV4 (Dr. Robot Inc., Markham, ON, Canada) platform was used as the moving system. The JaugarV4 is designed for indoor and outdoor applications requiring robust maneuverability and terrain maneuverability. The platform has four articulated arms that could convert the robot into various optimal navigation configurations to overcome different terrain challenges. For light crawlers, it has a slope crawling capacity of more than 55 degrees and a good soft ground driving and obstacle climbing capacity, which can suit the ground traffic demands of hilly and sloping orchards. At the same time, it integrates outdoor GPS and 9 DOF IMU (Gyro/Accelerometer/Compass) to obtain the accurate real-time three-dimensional position and attitude for autonomous navigation [53].

4.4.2. Shear Forklifting and Manipulator of the Robot Body

According to the demands of both vehicle body passing and space coverage in a closed citrus orchard, the technical combination of an electric multistage scissor lift with a manipulator with fewer degrees of freedom was designed. In order to meet the demands of the small body and the large vertical operation space of the robot, transverse electric multi-stage shear fork and elastic-assisted starting mechanisms were used for the shear forklifting mechanism to resolve the problem of the excessive initial starting torque in the shear fork of the transverse motor. In addition, a horizontal rotation degree of freedom was added between the base of the 2-DOF manipulator and the lifting platform to meet the demands of a flexible attitude change during picking.

4.4.3. End-Effector

According to the demands of picking citrus with a flat stem and reduced clamp damage, the technologies required for citrus clamping mainly include double spherical finger structures (CN213214398-U), airbag grasping (CN111937592-A), and pipeline swallowing structures (CN111972127A). From this technical combination, a robot end-effector for picking fruit with a flat stem was created. Its structure is shown in Figure 13. The new end-effector is composed of two spherical finger mechanisms, a knife swing mechanism, a pipeline airbag sucker structure, and a fruit delivery hose.

- The two spherical finger mechanisms are composed of a relatively symmetrical 1/4 spherical holding finger and a single-motor symmetrical transmission mechanism.

The two spherical fingers are symmetrically installed above the tube and driven to open and close by the motor in order to clamp the fruit;

- The knife swinging mechanism is a semicircular narrow knife, which is also installed above the tube, and swung upward and reset by the motor. The rotation axis is perpendicular to the rotation axis of the spherical finger, and the inner diameter of the semicircular narrow blade is consistent with the outer diameter of the sphere after the two spherical fingers have closed;
- An annular airbag is installed on the inner lower side of the tube body to swallow the fruit;
- The pipeline is connected to the hose for delivering the fruit under the airbag.

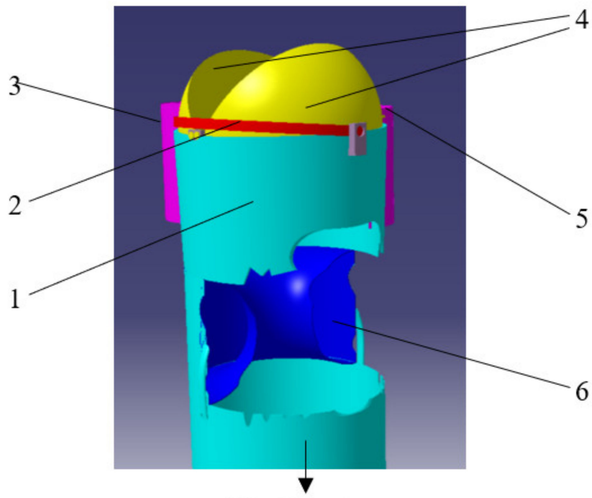


Figure 13. Structure of the new end-effector for a citrus picking robot meeting the demands of the spherical fruit and clamp damage reduction: 1, tube; 2, swing knife; 3, motor; 4, spherical finger; 5, motor; 6, airbag.

The airbag mechanism and the two spherical finger mechanisms can realize the rapid and flexible stem clamping of citrus fruit, and the combination of two spherical fingers and the semicircular narrow strip swing knife can realize the picking of the flat stem. Based on the combination of multiple technologies, the innovation can be realized, which can effectively meet the demands of flat stem picking in actual production. Meanwhile, the end-effector system is simple, reliable, and easy to control, which provides a greater possibility for practical production and application.

4.4.4. Discussion

With the technology recommendation results based on the TKG, a citrus picking robot was designed, where the system includes a crawl moving system, a shear forklifting system, a 2-DOF arm manipulator, and a new end-effector with a flat stem. By using the Realsense sensor, the identification of on-branch citrus fruit [54] and hand-eye coordination planning for the fruit picking robot was realized for the sensing and control function [55].

Recently, the citrus pick robot is mainly focused on the key component design and vision-based target recognition, etc. In the greenhouse, the robot was moved by the wheels [7] or a fixed track system [6], whereas, in the open field, the moving system was mainly based on the tractor [56] or unmanned vehicle [3]. However, on hilly and sloped terrain, especially in orchards, the structure of the tractor or unmanned vehicle is too large, and the function of the obstacle climbing is lacking. Therefore, a crawl moving system was used to both reduce the size of the robot and improve the ability of obstacle avoidance, and the shear forklifting system was used to meet the demands for the distance of the citrus tree.

In fact, for the specific nature of work in agriculture, robots have different design requirements [19,57], which are related to the shape of the fruit, the different degrees of ripeness, the ease of damage to the fruit, etc. [2,56,58]. In this research, the TKG mainly refers to the mechanical system, and the knowledge regarding the sensing and control system (target recognition, navigation, and control) for the agricultural robot is mainly published by the literature. Therefore, it is necessary to create a multi-source knowledge graph fusion for innovative agricultural robot design [17,59].

5. Conclusions

Traditionally, the design of innovative robot systems relies on the expertise or intuition of the designer, and faces high uncertainty [39]. In particular, agricultural robot design needs knowledge about agricultural cultivation, the electromechanical system, automatic control, etc. To inform and overcome design uncertainty, and provide multidisciplinary knowledge, in this study, a TKG for an agricultural robot design was established from patent information in order to realize the technology recommendations for the design of an agricultural robot.

(1) According to the IPC co-classification network of the agricultural robot patents, the path recognition method realized the design process of the different operation objectives and the operation scene;

(2) Through the TF-IDF keywords extraction model, the keywords of the patent document were revealed. Through the word co-occur network analyses, manual tagging, and expert interviews, the technological word library and the efficacy word library were constructed to establish the technology–efficacy map;

(3) To meet the demands of the agricultural robot's design, the patent TKG, the robot component TKG, and the design TKG were established to realize the technology recommendation process for the innovative agricultural robot design;

(4) The case of an innovative citrus picking robot design was realized to describe the design process. From the technology recommendation results based on the agricultural robot TKG, the moving system, body, and end-effector were designed to verify the recommendation results.

Although the technology recommendations for the agricultural robot design based on the patent TKG were realized, in this study, the patent documents were collected by manual retrieval, the technology and efficacy words were extracted by the TF-IDF model, and the recommendation process was only based on the TKG. NLP, machine learning, intelligent reasoning, and other intelligent artificial methods could be used for the agricultural robot TKG analyses and the technology recommendations [60–62]. In addition, published papers would be another scientific literature data source for the construction of the domain TKG and KG [63]. In the future, a multi-source knowledge graph fusion for innovative agricultural robot design is a possibility.

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