SEMARAK ILMU
PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Research Progress on Vision Guidance of Industrial Robots Based on Bibliometrics

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ARTICLE INFO

Article history:
Received 13 December 2025
Received in revised form 19 February 2026
Accepted 15 April 2026
Available online 7 May 2026

Keywords:
Industrial robot, Visual guidance, VOSviewer, bibliometrics

ABSTRACT

This paper provides a thorough bibliometric analysis of the evolution of visual guidance technology in industrial robotics from 1982 to 2024. The study examines patterns in publication trends, international collaboration, top contributors, and significant research themes using literature from the Web of Science Core Collection. VOSviewer (version 1.6) is used. 20), with a peak in publications in 2023, the analysis shows a steady increase in scholarly output. 4,226 authors, 1,164 institutions, and 65 countries or regions were represented in the 1,294 publications that were examined in total. The results show that intelligent and adaptive control systems are becoming more and more popular, which is indicative of the incorporation of computer vision, AI, and machine learning into robotic guidance. Improved accuracy, real-time responsiveness, obstacle navigation, and adaptability in challenging situations are noteworthy themes. Overall, this analysis provides insightful information about the direction of this field's research, pointing academics and industry professionals toward significant developments and future paths in industrial robot visual guidance.

1. Introduction

The manufacturing sector has been under tremendous strain due to the worldwide reduction in population dividends and the increase in production costs. As businesses look to cut costs and increase efficiency, integrating robots into manufacturing processes has grown in importance. Human workers are less burdened by robots' exceptional performance in hazardous and repetitive tasks [1–3]. Robots have developed into intelligent systems with the ability to perceive, coordinate, and make complex decisions daily. To mimic human or animal intelligence, these sophisticated robots now carry out intricate tasks like sorting and assembly. Their expanding use in a variety of sectors is

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https://doi.org/10.37934/araset.59.5.401418

revolutionizing contemporary manufacturing and reaffirming automation as a major force behind innovation and competitiveness.

Industrial robots play a crucial role in enhancing production efficiency, significantly influencing both quality and cost in manufacturing. A key distinction between intelligent and traditional automated robots lies in their ability to perceive and respond to dynamic environments. Unlike conventional computerised robots that operate based on predefined routines without adapting to environmental variations, intelligent robots incorporate advanced vision systems to recognize objects and autonomously determine optimal actions. Intelligent visual guidance technology is an artificial "eyesight" for robots, enabling real-time data acquisition through integrated sensors that process visual information using machine learning algorithms. This technology enhances operational flexibility and accuracy by allowing robots to determine task execution strategies rather than merely following preprogrammed instructions. Implementing intelligent visual guidance has expanded the functional scope of industrial robots, improving adaptability to complex industrial production tasks. To provide valuable insights into research trends in this domain, this study presents a bibliometric analysis of visual guidance technology in industrial robots, offering a comprehensive reference for scholars and researchers engaged in related fields.

2. Literature review

A deep learning-based visual sharing method for networked robots that emphasized human-robot interaction technology and data transmission was done by Xiao in 2020 [4]. Meanwhile, Kong completed the application of visual guidance technology in industrial robots in 2021[5]. His technique provides a vital prerequisite for promotion to more perception and more intelligent levels. At the same time, Peng and Chen [6] also proposed a vision-based method for industrial robot fault detection that eliminates the need for communication protocol for real-time monitoring. Zhao *et al.,* [7] further exhibited their vision-based seam tracking technique with a laser that contributes to a more robust and practical application for welding tasks. In addition, Karabegović *et al.,* [8] investigated global patterns of industrial robot's use, including traditional and collaborative robots per continent and sector. The visual perceptual system is the first part of a welding robot, and spatial sensing methods are distinct from perception mechanics monocular, binocular and multi-view vision methods were classified [9]. As summarized in previous studies, applications, from fault detection to smart gripping and seam detection, are being pursued where correct reasoning by robots is essential. So, this suggests that many of these rely on computer vision, deep learning or any of the new technologies to improve the performance parameters of industrial robots.

Machine vision and its variations are gaining popularity in a broader sector [10]. The use of machine vision systems in the precision cultivation of crops. Yan *et al.,* [11] explored the advancements in visual-based recognition and localisation methods for fruit-picking robots. Few studies have focused on other features of industrial robots. The positioning accuracy of industrial robots has been investigated with uncertain variables and presented as a reliability analysis using methods including Monte Carlo simulations and experimental-based methods [12]. An unsupervised anomaly detection method employing a sliding window convolutional variational autoencoder, allowing condition-based maintenance for industrial robots, was developed [13]. Additionally, Huynh *et al.,* [14] presented a multibody dynamic model for articulated industrial robots involved in machining operations where knowing key parameters is crucial to the optimal functioning of the robotic processes. The evolution of the robotics part of Industry 4.0: Collaborative robots' role [15]. Tseng *et al.,* [16] introduced a method that integrates bibliometric analysis and the fuzzy Delphi method to review sustainable industrial and operations engineering in the context of Industry 4.0

transition steps. Following suit, Tan *et al.,* [17] archived a bibliometric study intending to explore the development evolution of green energy and environmental technology through information visualization techniques. In summary, this paper demonstrates the variety of machine vision and industrial robot applications in different sectors by providing insights into other systematic mapping and bibliometric studies and discussing trends, challenges, and gaps in both fields over two years. The variety of applications this combination of easy-to-replace parts and guidance into new environments can bring to factory floors is promising [18].

3. Methodology

3.1 Data Export

In this study, the authoritative database Web of Science (WOS) Core Collection (Science Citation Index Expanded, SCIE) was used as the data source. The literature search was conducted using the following custom advanced search query: (TS=("industrial robot" OR "industrial robots" OR "industry robot" OR "robot" OR "robotic manipulator" OR "industrial robot industry" OR "industrial robotics" OR "robotics" OR "industrial manipulator" OR "industrial six-axis machine" OR "industry manipulator" OR "robots" OR "mobile industrial robot" OR "industrial robot kinematics" OR "robotic" OR "industrial glue robot" OR "Mitsubishi industrial robot" OR "industrial manipulators" OR "Chinese industrial robot" OR "industrial welding robot" OR "industrial robotic" OR "industry robotic" OR "intelligent industrial robot" OR "industrial robots" OR "arc-welding industrial robot" OR "industry robots" OR "industrial reduced model robot")) AND TS=("visual guide" OR "vision guiding" OR "visual navigation" OR "vision-guided" OR "visual guidance" OR "visual guided" OR "visual guiding" OR "visual guidance system" OR "visual servo" OR "vision guiding technique" OR "machine visual-guided" OR "vision guide" OR "vision guidance"). The search covered the period from January 1, 1982, to August 28, 2024. After screening and removing duplicate records, a total of 1,293 relevant publications were obtained, and the retrieved documents were exported in txt format.

3.2 Data Analysis

For analysis, this study chooses VOSviewer software. Developed by Dr Ness Jan van Eck and Dr Ludo Waltman from the Centre for Science and Technology Studies (CWTS) at Leiden University, Netherlands [19]. VOSviewer was released in 2009 to build visual bibliometric networks [20]. It combines bibliometric techniques like citation analysis, bibliographic coupling, co-citation analysis, co-word analysis and clustering analysis incorporated by the software on raw data from literature databases such as Web of Science, Scopus, Dimensions and PubMed. The bibliometric data was analysed visually for publication volume, authors, institutions, countries, journals and keywords using terms frequency analysis and clustering analysis with VOSviewer software (version 1.6.16). The study built different kinds of knowledge networks, such as collaboration networks, co-word networks, and co-citation networks. Microsoft Excel was used to process data and based on statistical results and the degree of association, the research hotspots in the application of visual guidance technology in industrial robots were summarized.

4. Results

4.1 Publication Trends and Descriptive Analysis

According to the Web of Science (WOS) database, these 1,293 papers have been cited 28,142 times, with 26,376 of these citations being independent of self-citations. The H-index is 74, and the average number of citations per paper is 21.76. These 1,293 publications indicate a growing interest in the topic of visual guidance technology for industrial robots. Although the first publication on this topic appeared in 1982, it was not until 1994 that the number of publications began to grow exponentially. Prior to 1994, the growth rate was minimal, but since then, the number of publications has increased from 8 in 1994 to 130 in 2023. However, the number of publications in 2024 saw a slight decline, with a total of 112 publications. The number of scholarly works on visual guidance for industrial robots is expected to increase in the coming years. Figure 1 shows the number of articles published and their corresponding citations from 1982 to 2024.

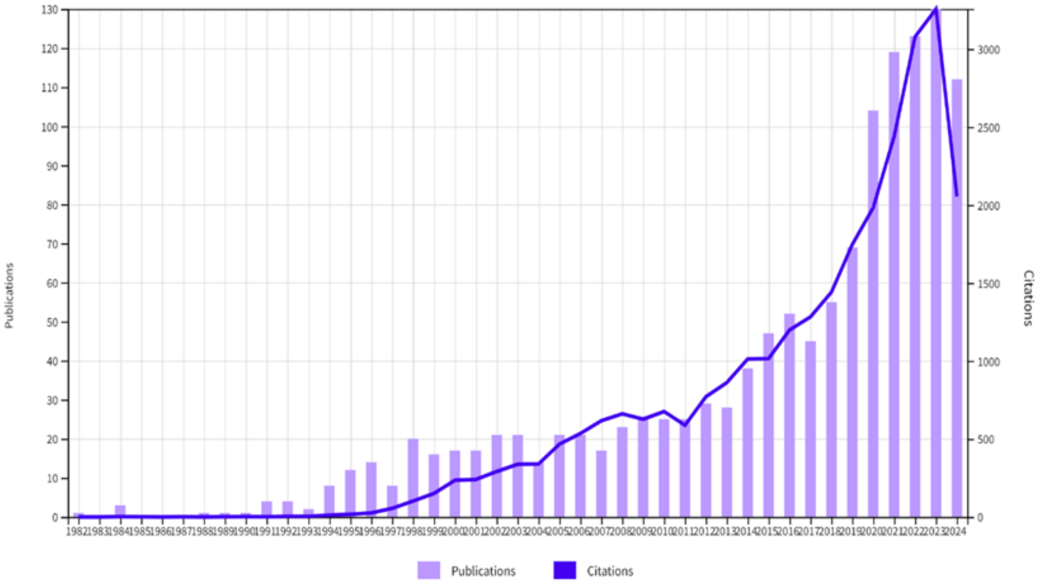

Fig. 1. Number of articles published from 1982 to 2024 and their corresponding citations.

4.2 Countries/regions Collaboration Analysis

The map in Figure 2 depicts global research collaborations between various countries/regions. The 1,293 papers retrieved from the Web of Science (WOS) database come from 65 countries. China is the most dominant node in the visualization, indicating its substantial presence in research collaborations. Therefore, the number of global research collaborations from China is 542 papers. The node's size means its high number of publications and active participation in international research projects. This trend aligns with China’s increasing research funding, technology advancements, and international collaboration strategies. While China is expanding its influence, the USA and European nations (such as Germany, France, England) continue to play a pivotal role in international research. Their well-established institutions, research funding opportunities, and global partnerships facilitate their strong presence in global research collaborations. The smaller nodes indicate moderate international research collaboration compared to the leading countries, such as India, Malaysia, and Brazil. It was noted that these countries have their connections with larger nodes. Therefore, these countries may present growing research contributors, steadily increasing their global academic presence.

The colorful lines that link the nodes in the visualization show the research collaborations between different regions/countries. Each color signifies a distinct cluster, grouping countries based on strength and frequency of their research interaction. As shown in Figure 2, the cluster theme describes the relationships in global research collaboration. Looking at Figure 2, it is noticeable that China, Japan, South Korea, and Singapore are in the green cluster. These are the most prominent Asian contributors to global research collaboration. It is also evidence that the red cluster, consisting of the United States, France, Spain, and Mexico, had close academic interactions in North America and Europe. These countries possibly have frequent and intensive research interaction.

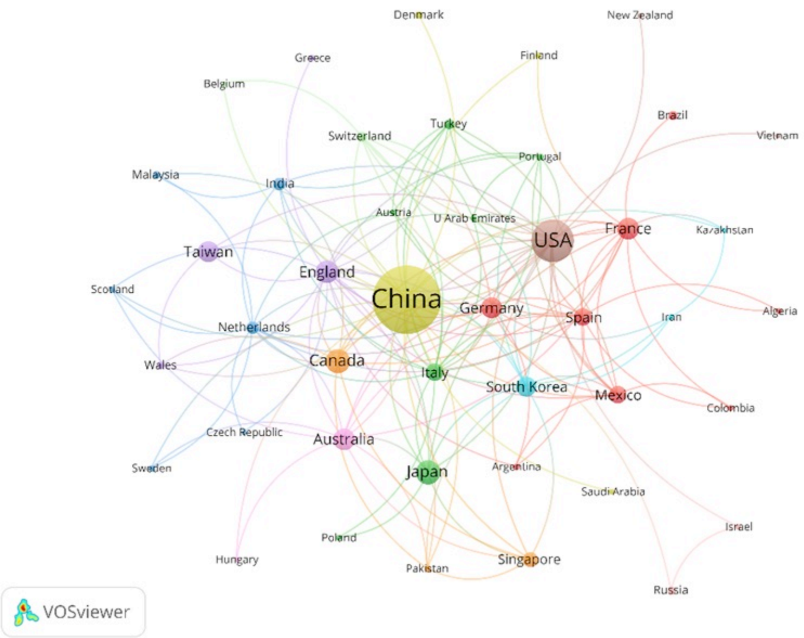

Fig. 2. Analysis of country/region cooperation.

4.2 Institutional Collaboration Analysis

The map in Figure 3 illustrates the global research collaboration among various institutions. The analysis which is pictured in Figure 3 highlights the major contributors in terms of research output and their international linkages. A collaboration network map of institutions was generated using research institutions as nodes and setting a minimum threshold of six papers per institution, as shown in Figure 3. A total of 75 institutions met this threshold. The 1,293 papers retrieved from the Web of Science (WOS) database originated from 1,164 research institutions.

The analysis reveals that Chinese institutions, notably the Chinese Academy of Sciences, Shanghai Jiao Tong University, and The Chinese University of Hong Kong, play a central role in global research collaborations. Their significant node size indicates a high volume of publications and extensive research partnerships. It has to be noted that the strong connections among these institutions have led to a robust academic network within China and beyond. Table 1 lists the top ten institutions by publication volume. Universities in the USA, such as Carnegie Mellon University, Johns Hopkins University, and the University of Florida, also collaborate the most with Chinese institutions, in addition to the number of publications. It was noted that strong collaborations will lead to active academic exchange and joint research initiatives in various fields.

While dominant institutions form strong research hubs, emerging universities from developing countries, such as India and Malaysia, exhibit growing academic collaborations. These institutions are gradually integrating into the global research network but remain less prominent compared to leading universities. Strengthening research infrastructure and fostering international partnerships could enhance their visibility and impact.

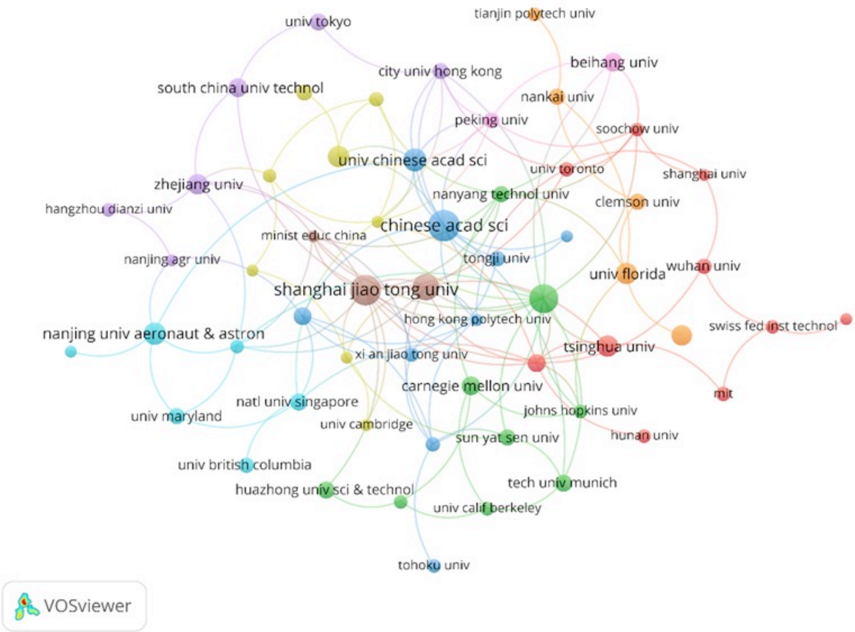

Fig. 3. Analysis of Institutional Cooperation.

Table 1
Top ten institutions with the highest number of publications

Rank	Institution	Documents	Total link strength
1	Chinese Academy of Sciences	38	31
2	Shanghai Jiao Tong University	36	28
3	The Chinese University of Hong Kong	31	30
4	Harbin Institute of Technology	27	22
5	University of Chinese Academy of Sciences	20	26
6	Nanjing University of Aeronautics and Astronautics	19	9
7	Australian National University	17	8
8	Tsinghua University	17	6
9	University of Florida	17	10
10	University of Illinois	16	2

4.3 Author Collaboration Analysis

The visualization generated using VOS viewer represents the author collaborations network among researchers, illustrated in Figure 4. The map is studied by setting the authors as nodes and setting a minimum threshold of four publications per author. After the screening process, only 90 authors met this criterion. This map displays the most prolific authors that have the most publications. Each node in the figure represents an author. The node size reflects the number of publications, while the lines between nodes indicate collaborative relationships. The colors represent clusters of closely related collaborative authors, identified based on the co-authorship relationship. The size of a node corresponds to the number of publications or citations an author has, with larger nodes representing more prolific or highly cited researchers. Larger nodes, such as Li Weibing and Wang Hesheng, have a higher number of publications. Thus, they have become prominent members of their respective research communities. Conversely, smaller nodes indicate authors with relatively fewer publications.

The connecting lines between authors represent co-authorship relationships. The link between nodes is shorter and thicker when the authors have a stronger collaboration, to be exact, multiple joint publications between authors and their networking authors. It was noted that in Figure 4, Li Weibing and Li Zheng have a well-established research partnership, as evidence by the dense network of connections in their cluster (green cluster). In contrast, some nodes are loosely connected. This is owing to those authors having fewer collaborative publications.

From the visualization, it is proven that specific authors serve as key hubs in their respective networks. For instance, Wang Hesheng appears to be well-connected to multiple research clusters. Different clusters indicate that the authors come from different specializations of research interests. For example, Wang Hesheng and Chen Weidong in the blue cluster likely focus on a different aspect of the research area compared to the orange cluster (Zhang Xuebo and Li Baoquan).

A collaboration network map of institutions was generated using research institutions as nodes and setting a minimum threshold of six papers per institution (Figure 3). A total of 75 institutions met this threshold. The 1,293 papers retrieved from the Web of Science (WOS) database originated from 1,164 research institutions. The top three institutions by the number of publications are the Chinese Academy of Sciences (38 papers), Shanghai Jiao Tong University (36 papers), and The Chinese University of Hong Kong (31 papers), as shown in Figure 3a. In the institutional collaboration network map (for institutions with ≥6 papers), each node represents a research institution, with the node's size proportional to the number of publications and the lines between nodes indicating collaboration between institutions. Table 2 lists the top ten institutions by publication volume.

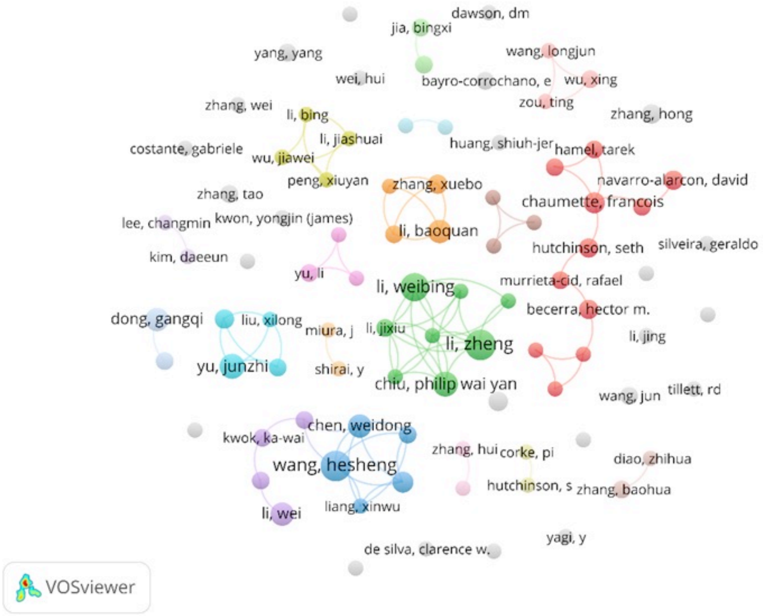

Fig. 4. Author collaboration analysis.

4.4 Citation Collaboration Analysis

The author collaboration network illustrated in Figure 5 reveals distinct clusters of authors working within visual servoing, robotics, and computer vision. These clusters are formed based on co-authorship, reflecting the strength and frequency of research collaboration. Apart from co-authorship, the impact of citations can also be inferred from the connectivity and prominence of authors. Looking at Figure 5, it is observed that Chaumette *et al.,* [21] in the blue cluster is the author with the most highly co-cited primary research areas, including robotic vision, visual servoing, robotics, and computer vision. This author also has a strong network tie with researchers such as Chen *et al.,* [13] and Wang Y *et al.,* [22] highlight a focus on visual tracking and motion control in robotics.

Dense interconnections suggest that this group has significantly contributed to practical applications in real-world robotic implementations. Cluster red represents a highly interconnected group centered around Malis *et al.,* [23], Hutchinson *et al.,* [24], [25] and Espiau *et al.,* [25]. These authors have a common research similarity, visual servoing. The dense connections suggest that this cluster has contributed extensively to fundamental theories and methodologies, as evidenced by frequent co-authorship. Lowe [26], Bay *et al.,* [27] and He *et al.,* [28] in the green cluster represent research in computer vision, particularly in feature extraction and deep learning-based methodologies. The yellow cluster, led by Srinivasan [29] is more loosely connected, indicating a relatively minor but more focused research community. The analysis reveals that research in robotics and automation, particularly in visual servoing and computer vision, is characterized by strong collaboration networks. Influential authors can be seen by their frequent collaborations and high citation counts, for example, Chaumette Francois *et al.,* [21], Malis *et al.,* [23], and Hutchinson *et al.,* [24]. It is evident from this map that while traditional robotics remain dominant, deep learning-based approaches, such as those developed by, He *et al.,* [28], and Yu [30] are becoming more prominence, indicating a shifting research trend.

Therefore, it can be concluded that the author's collaboration and citation analysis collectively highlight the evolution of research in robotics and computer vision. The field is characterized by strong interconnectivity, with specific key figures acting as pivotal contributors. While visual servoing remains as a dominant topic, integrating deep learning methods signals an ongoing transformation in the field. Future research will likely witness more interdisciplinary collaborations, particularly between robotics and artificial intelligence.

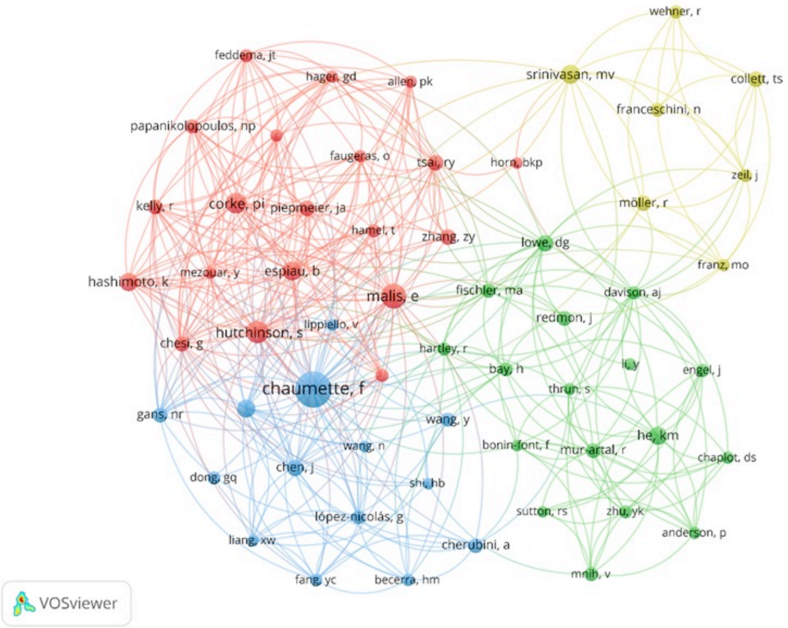

Fig. 5. Author citation analysis

4.4 Co-citation Analysis

The co-citation analysis provides insight into the intellectual structure of the research field by identifying clusters of frequently co-cited documents. The visualization generated using VOS viewer reveals distinct groups of citations, each representing a different thematic area within the broader domain. The clusters are represented by red, green, and blue. These clusters indicate strong citation relationships among sets of publications. As can be seen from the map, the green cluster is likely to become a central figure in visual servoing and robotics. This cluster contains foundational research on visual servoing, robotic perception, and control. The most frequently co-cited document is Chaumette *et al.,* [21], with the highest citation count of 160. Other influential papers in the same cluster are Hutchinson *et al.,* [24] and Espiau *et al.,* [25], which lay the groundwork for visual servoing and robotic controls. The strong interconnection of the research in this area has evolved from theoretical frameworks to practical implementations in robotic vision systems.

The co-citation analysis included only references cited 20 times or more, as the citation threshold was set at 20. This approach ensured that the study focused on the most significant and relevant topics in the scientific literature, identifying 52 references that met or exceeded the co-citation frequency criteria. Figure 6 presents the co-citation network map of the literature on visual guidance in industrial robots. As can been seen in the figure, the network is divided into distinct clusters, which are red, blue and green. Each cluster represents a group of authors who frequently co-author paper together.

The red cluster in Figure 6 highlights a significant paradigm shift from classical vision-based approaches to deep-learning-driven methodologies, particularly in simultaneous localization and mapping (SLAM) and reinforcement learning, which have enhanced robotic autonomy. Early research in image processing, feature detection, and object recognition by Otsu [31], Fischler & Bolles [32], and Lowe [26] laid the foundation for computable visual input analysis, enabling robots to interpret objects in structured environments. However, advancements by Krizhevsky *et al.,* [33] and He *et al.,* [28] demonstrated the transformative impact of deep learning, particularly convolutional neural networks (CNNs), in automating visual information processing, significantly improving object recognition and classification. The evolution of SLAM, as documented by Davison *et al.,* [34] and Mur-Artal *et al.,* [35], underscores the increasing sophistication of vision-based navigation, allowing robots to map and track environments with remarkable accuracy. Reinforcement learning, as pioneered by Mnih *et al.,* [36] and further explored by Sutton and Barto [37], enhances decision-making capabilities, enabling robots to learn optimal actions through iterative interaction with their surroundings. Despite these advancements, real-world applications remain challenging due to environmental variability, necessitating the development of robots feature identification algorithms, such as those proposed by Bay *et al.,* [27] and Rublee *et al.,* [38], to ensure reliable object recognition under diverse conditions. The integration of these technologies has led to the emergence of highly autonomous robotic systems, as explored by Bonin-Font *et al.,* [39] and Savva *et al.,* [40], who emphasize bridging theoretical advancements with practical implementations for industrial applications. This cluster underscores the convergence of deep learning, SLAM, and reinforcement learning as a well-established strategy that enhances accuracy, robustness, and operational efficiency, enabling industrial robots to perform complex tasks with minimal human intervention, thus increasing flexibility and productivity in modern manufacturing environments.

While for the green cluster, it was primarily focused on the integration of visual servoing capabilities within advanced control frameworks for industrial robots, reflecting a shift toward more sophisticated, precise and adaptive robotic systems. Visual servoing, which utilizes visual data to guide robotic motion, has evolved significantly from its foundational frameworks to encompass image-based and position-based methods that correlate robot movements with real-time visual input, facilitating tasks such as object manipulation and industrial tracking [41- 43]. This paradigm shifts from conventional control techniques to advance nonlinear control methods is exemplified by the work of Malis *et al.,* [44], Malis *et al.,* [23], and Gans *et al.,* [45], who enhanced visual servoing robustness against environmental variations, particularly changes in lighting and object appearance, challenges frequently encountered in industrial setting. Further advancements were achieved through the integration of visual servoing with robust control systems, as explored by Luca *et al.,* [46], who replaced traditional PD/PID controllers with sophisticated feedback loops, ensuring system stability and reliability under uncertain conditions. This integration is crucial in industrial environments where unpredictable disturbances demand precise and adaptive robotic control. Expanding on this, Wang *et al.,* [47] and Lopez-Nicolas *et al.,* [48] combined visual servoing with mechanical control theories, significantly enhancing the complexity of robotic tasks sush as automated assembly and high-precision inspection. Studies by Hamel *et al.,* [49] and Piepmeier *et al.,* [50] further examined the real-world deployment of these techniques, addressing critical challenges such as occlusions, dynamic illumination changes, and the necessity for real-time processing.

In industrial applications requiring high accuracy and reliability, adaptive visual servoing plays a pivotal role in enabling robots to perform consistently under dynamic conditions. The effectiveness of such methods has been demonstrated by Liu *et al.,* [51] and Mariottini *et al.,* [52] improving robotic efficiency and speed in practical applications, including assembly lines and metrology inspections. Ultimately, this cluster underscores the growing importance of integrating visual servoing with advanced control strategies to enhance industrial robotics' autonomy, precision, and adaptability. As industrial processes continue to evolve in complexity, leveraging visual input alongside robust control methodologies enables the development of intelligent, self-sufficient robots capable of executing intricate tasks with minimal human intervention, thereby improving manufacturing efficiency and reliability.

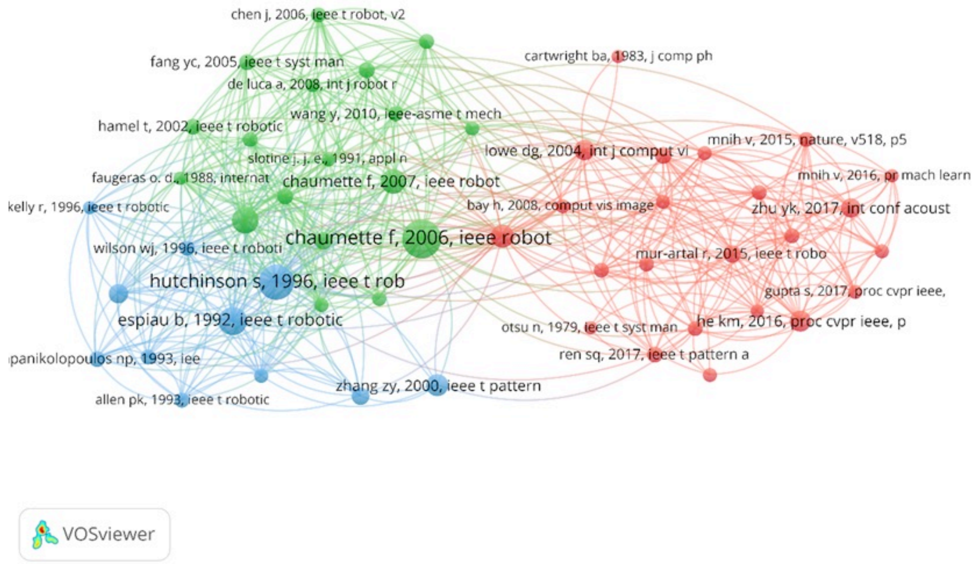

Fig. 6. Co-citation analysis of literature.

Research that focuses on advancing vision-guided industrial robotics by refining visual servoing, camera calibration, and 3D vision methods to enhance robotic precision and adaptability in complex environments. Visual servoing, pioneered by Hutchinson *et al.,* [24] and foundationally explored by

Espiau *et al.,* [25] and Khosla *et al.,* [53], integrates real-time visual feedback into control system, significantly improving robotic manipulation, object tracking, and assembly tasks. Accurate camera calibration, as developed by Ma *et al.,* [54] and Zhang [55], ensures precise alignment between visual data and real-world measurements, enabling robots to perceive and respond to their surroundings with high fidelity. Faugeras [56] further advanced 3D vision, providing critical insights into spatial cognition, essential for robotic navigation and interaction with dynamic environments. The integration of these technologies enhances robotic stability and efficiency, particularly in industrial applications requiring precision under variable conditions Feddema *et al.,* [57], Kelly [58]. Practical implementations of visual servoing, as demonstrated in assembly and inspection processes, have underscored its effectiveness in improving robotic accuracy while addressing real-world challenges such as lighting variations and occlusion Weiss *et al.,* [59], Wilson *et al.,* [60]. As industrial automation demands greater precision with minimal human intervention, the continued evolution of visual servoing, robust control integration, and adaptive calibration techniques remains pivotal in developing next-generation intelligent robots capable of executing intricate tasks autonomously, ultimately redefining efficiency and reliability in modern manufacturing.

4.5 Keyword Co-Occurrence Analysis

The keyword co-occurrence analysis illustrated in Figure 7, reveals analysis reveals four primary research clusters in vision-based robotics which are visual servoing, robotics and mobile robots (red cluster), robotic systems and vision sensors (blue cluster), visual navigation and autonomous systems (green cluster), and task analysis and training (yellow cluster). Looking at Figure 7, visual servoing, target tracking, and adaptive control that focus on real-time robotic control are in the red cluster, which is critical for increasing robot agility in unstructured environments. The blue cluster emphasizes robot vision systems, calibration and industrial robotics, highlighting the importance of precise sensing technologies for robotic actuation and control. The green cluster is centered on visual navigating, obstacle avoidance, reinforcement learning, and autonomous robots, signifying the growing role of AI-driven perception in self-navigating systems, while the yellow clusters more to the visualization, feature extraction, and training, crucial for cognitive and algorithms improvement in robotic task execution. It was noted that each cluster represents critical subdomains with significant interconnections. The red and green clusters which are visual servoing and visual navigation exhibits strong interconnectivity through mobile robot and computer vision, indicating that real-time-vision- based control is crucial for both stationary and mobile robotic platforms. Similarly, the blue and yellow clusters which are robotic systems and task analysis show notable interaction, reflecting the importance of sensor technologies in improving robotic perception and task efficiency. Strong interconnection will increase reliance on deep learning, neural networks, and sensor fusion to enhance robotic intelligence and autonomy, particularly in industrial, medical and autonomous navigation applications.

As the discussion above, the red cluster highlights the convergence of industrial robotic vision guidance, advanced control strategies, machine vision, and artificial intelligence (AI) to enhance the autonomy, precision, and adaptability of robotic systems. A key area driving this transformation is visual servoing, including image-based visual servoing and visual servo control, which utilizes visual feedback to regulate and guide real-time robot motion. These approaches, primarily dependent on image processing and machine vision technique, enable robots to perceive and interpret their surroundings, facilitating tasks that require high precision, such as trajectory tracking, object tracking, and pose estimation [61]. A particularly promising advancement is uncalibrated visual servoing, which enhances the adaptability of industrial robots by eliminating the need for perfectly calibrated vision systems, making them more effective in dynamic environments [62]. The rapid integration of AI and neural networks has further revolutionized robotic systems, allowing robots to autonomously handle tasks such as object recognition, posture estimation, and path planning through deep learning models [63]. Neural networks empower robots with the ability to learn from their surroundings, enabling them to adjust their decision-making processes and enhance their responsiveness. In addition, adaptive control mechanisms, particularly Kalman filters, contribute to stabilizing robot movements while dynamically adjusting to environmental changes [64]. This fusion of AI, adaptive control and visual feedback significantly improves the resilience and versatility of robotic systems. This cluster underscores the seamless integration of AI-driven perception, adaptive control, and advanced visual processing, paving the way for next-generation robotic systems that achieve higher autonomy, dexterity, and precision. As these technologies continue to advance, they will further drive automation in diverse industrial applications, reducing human dependency while enhancing efficiency and operational capabilities.

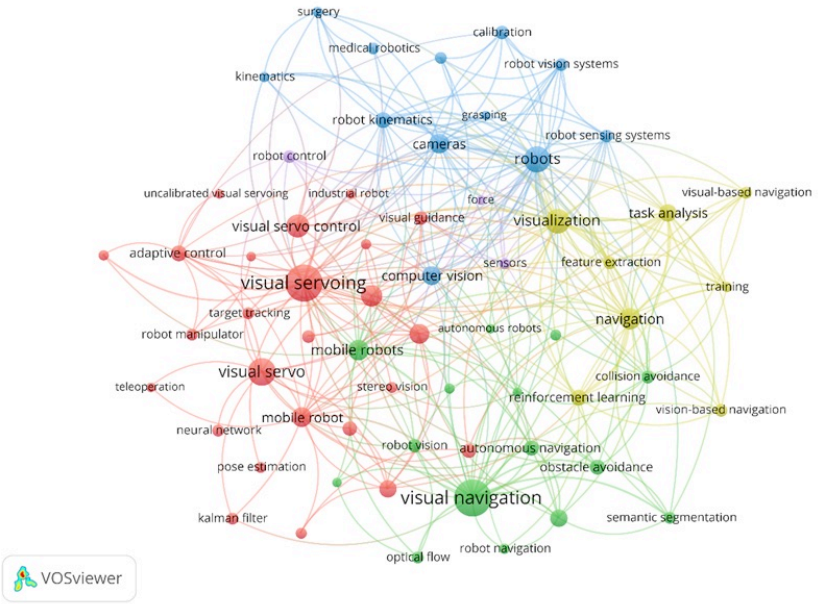

Fig. 7. Keyword co-occurrence analysis

While for the green cluster, it explores the advancement of autonomous robots in complex, dynamic environments, emphasizing AI-driven visual perception for real-time decision-making. The integration of deep learning and deep reinforcement learning has significantly enhanced robot autonomy, navigation, and obstacle avoidance. Techniques such as semantic segmentation and visual tracking improve environmental comprehension, allowing robots to detect and avoid these abilities, enabling robots to optimize navigation strategies through interaction with their surroundings [65-67]. In industrial settings, robots must maneuver around dynamic obstacles, using optical flow and vision-based techniques to enhance adaptability [68]. Mobile robots leverage AI-driven vision systems to perform tasks like material handling, inspection, and delivery [69], while drones and aerial robots utilize deep learning for autonomous surveying and environmental monitoring [70]. The application of deep learning and optical flow algorithms ensures stable flight paths and obstacle avoidance [71]. As AI-driven visual perception continues to evolve, robots are becoming increasingly capable of performing complex tasks with minimal supervision, driving greater intelligence, flexibility, and autonomy in industrial automation [72].

The blue cluster emphasizes the critical role of calibration in robotic precision, particularly in hand-eye coordination for industrial and medical applications. Accurate calibration ensures a robot's visual system aligns with its physical capabilities, enabling precise interaction with its environment [73]. Inadequate calibration can lead to misinterpretation of spatial data and imprecise motion control [74]. In robotic kinematics and sensing systems, calibration synchronizes positional data from cameras, lasers, and sensors with robotic motion [75]. This is crucial in factory assembly and surgical robotics, where extreme accuracy is required [76]. Computer vision algorithms, combined with precise calibration, enhance robot's ability to grasp, manipulate, and perform delicate tasks autonomously [77]. In medical robotics, hand-eye calibration is vital for minimally invasive surgeries, ensuring precision in tasks like tissue manipulation and suturing [78-79]. Similarly, industrial robots rely on calibrated vision systems for high-precision operations like pick-and-place automation [80]. Advanced robotic sensing systems integrate multiple sensors and cameras, requiring meticulous calibration to enhance environmental awareness [61].

While precise calibration, particularly hand-eye coordination, ensures accurate robotic perception and movement of the robot in the blue cluster, genuine autonomy requires continuous learning and adaptation. This is where reinforcement learning and vision-based navigation in the yellow cluster come into the scene, allowing robots to refine their movements, respond dynamically to changing environments, and operate independently in complex environments. The yellow cluster and purple cluster have a common theme of autonomous system. However, the purple cluster focuses on enhancing robot safety, accuracy for complex industrial applications. For example, in collaboration with robotics, force sensing ensures safety by detecting sudden force changes and adjusting movements to prevent collisions [81]. Applications in medical robotics, complex assembly, and hazardous environments demand precise force control [82-84]. As robotic control evolves, integrating force sensors with other sensory inputs will enable robots to perform delicate tasks with greater precision, improving industrial productivity and safety.

5. Conclusions

This study utilized VOSviewer software to analyse literature related to visual guidance for industrial robots retrieved from the Web of Science Core Collection database. The research landscape and trends in visual guidance for industrial robots were presented as knowledge maps. The results indicate a steady increase in research interest in this area, with studies primarily focusing on industrial robots and machine vision. These findings hint that intelligent visual guidance technology has enhanced industrial robots and made them applicable in dynamic workspaces. Notwithstanding, intelligent visual guidance technology needs to be improved in stability, and there is still a long way to go in hardware technology that continuously adjusts and optimizes visual algorithms to push the intelligence of industrial robots to a new high. However, this study has a limitation. Such as the WOS database, which only includes a certain number of publications from reputable journals, and this has strengthened the low quality of analysis. Subsequent studies may widen the analysis by utilizing additional databases to deepen its texture and enhance its quality.

Acknowledgement

This research was not funded by any grant.

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