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Review

Recent Synergies of Machine Learning and Neurorobotics: A Bibliometric and Visualized Analysis

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Abstract: Over the past decade, neurorobotics-integrated machine learning has emerged as a new methodology to investigate and address related problems. The combined use of machine learning and neurorobotics allows us to solve problems and find explanatory models that would not be possible with traditional techniques, which are basic within the principles of symmetry. Hence, neuro-robotics has become a new research field. Accordingly, this study aimed to classify existing publications on neurorobotics via content analysis and knowledge mapping. The study also aimed to effectively understand the development trend of neurorobotics-integrated machine learning. Based on data collected from the Web of Science, 46 references were obtained, and bibliometric data from 2013 to 2021 were analyzed to identify the most productive countries, universities, authors, journals, and prolific publications in neurorobotics. CiteSpace was used to visualize the analysis based on co-citations, bibliographic coupling, and co-occurrence. The study also used keyword network analysis to discuss the current status of research in this field and determine the primary core topic network based on cluster analysis. Through the compilation and content analysis of specific bibliometric analyses, this study provides a specific explanation for the knowledge structure of the relevant subject area. Finally, the implications and future research context are discussed as references for future research.

Keywords: machine learning; robotics; bibliometric analysis; visualized analysis; neurorobotics-integrated machine learning

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1. Introduction

In the late 1980s, Kawato and Gomi [1] and Miyamoto et al. [2] first proposed an approach using neurorobotics to construct a series of robotic devices that investigated the adaptation of the cerebellum to motion. Since the mid-twentieth century, neuroscience has proven the significance of neurorobotics in several fields (for example, computer vision) based on its development in robot learning [3]. Notably, artificial intelligence (AI) is vital to computer vision because it facilitates deep learning [4]. AI research tools include machine learning (ML), artificial neural networks, fuzzy logic, adaptive-network-based fuzzy inference systems, genetic algorithms, pattern recognition, clustering, deep learning, and particle swarm optimization [5], which are closely associated with computer vision. For example, in automatic driving, combining deep learning technology with visual sensing makes the relevant systems more intelligent [3]. Moreover, models, algorithms, and technologies for ML have been developed and applied in numerous fields, such as data mining, pattern recognition, signal processing, and robot control. For example, Li [6] investigated the combination of ML and radar signal recognition; this approach significantly improved the accuracy of radar signal recognition and demonstrated good stability. Meanwhile, Ge et al. [7] suggested that "as a computational engine for data mining and analytics, ML serves as a basic tool for information extraction, data pattern recognition, and predictions". Owing to its significant potential, ML is essential for executing challenging robotic tasks [8].

Therefore, in the current study on ML, previous developments in computer vision were reviewed further to understand the overall changes and history of the field to facilitate future studies.

Currently, AI is widely used in medicine, calculations, engineering, science, finance, education, economics, and agriculture [9–13]. Notably, previous studies on intelligent robots based on ML have been extensively applied to medicine. For example, as a robot "with diabetes", Robin offers dual benefits of therapeutic effects and emotional support when managing children with diabetes [14]. Meanwhile, NEUROExos, a rehabilitation robot, can aid in physical rehabilitation and has been proposed to facilitate high-intensity therapy, including repetitive motions of damaged limbs. Thus, robots can help patients undergo more effective and stable rehabilitation processes and reduce the workload of therapists [15]. Basílio et al. [16] used bibliometrics to analyze 23,494 studies on multi-standard methods from 131 countries over the past 44 years to help understand the global evolution of the creation and use of multi-standard decision-making methods. In addition, an artificial electronic synapse has to be designed to imitate the behavior of the nervous system, owing to its essential features, which can receive excitatory signals and return informative synaptic reactions to the motor system. Therefore, such imitation can fundamentally broaden the horizons of artificial neurorobotics and learning systems [17]. The combination of neural robots and ML completely subverts traditional ML. Generally, ML-based methods are used to understand information processing in parallel and distributed neural architectures to effectively integrate the application of computational biology, natural language processing, and AI.

Neurorobotics is an emerging field that integrates neuroscience, AI, and interdisciplinary techniques. Among the traditional research topics related to robots, only topics related to robot path planning [18] and research on the trends and hotspot analysis of rehabilitation robots are available [19]. However, robotics and ML are topics of interest that have gradually received attention from several journals in recent years, including the special issue "Artificial Intelligence & Robotics" of the Advanced Robotics journal in 2019, Frontiers in Neurorobotics 2022 Special Issues "Robust Artificial Intelligence for Neurorobotics" and "Robust Artificial Intelligence for Neurorobotics", and a Special Issue of Sensors in 2022 "Neuro-Robotics Systems: Sensing, Cognition, Learning, and Control". Therefore, in this field, the application of neurorobotics has also received increasing attention in recent years; however, the research on comprehensive related topics and bibliometrics has not been systematically analyzed, and the processes adopted in the field have not been discussed. Therefore, herein, to better understand the development of ensemble ML for neural robots and to comprehensively explore its trends, bibliometric data references in science citation index (SCI) journals from 2013 to 2021 and key information from these academic publications were analyzed. This study further analyzed the current development of neurorobotics-integrated ML and the research methods applied in the field. This research used bibliometric methods and CiteSpace software to study and analyze the research topic and trends in this field, hoping to address the following questions: (1) What is the current state of ML and neurorobotics research and the status of journal publications? (2) What is the status quo of highly cited neurorobotics and ML research, and how have the related keywords, research areas, and authors evolved? Through research in important journals, we developed a preliminary understanding of the research on neurorobotics and ML and the prospects of the field.

Specifically, this study has the following three main contributions: (1) Through a literature review, the basic statistical characteristics of machine learning and neurorobotics, including the annual publication of papers, the publication of journals, and highly cited papers, are reflected; (2) keywords are searched on the Internet to find relevant published papers; these papers are discussed and analyzed to identify the topics of a specific field and the trend of changes in such topics over time; (3) lastly, through the analysis of content and topics, we learn about the preferred research directions and relevant applications of machine learning and neurorobotics.

The remainder of this paper is arranged below: Section 2 centers on the application of bibliometrics in past research. Section 3 explores data analysis and methodology, including data collection methods and the algorithms employed. Data results are discussed in Section 4, including basic characteristics, highly cited research, institutional cooperation networks, the results of analysis of keywords on the Internet, as well as content analysis. Lastly, Section 5 concludes the research, including research results, future research directions, and limitations.

2. Literature Review

Typically, bibliometrics is used for quantitative research and evaluating academic achievements, groups, and individuals involved in scientific research [20]. Bibliometric indicators enable readers to organize data [21] and more conveniently analyze the distribution, structure, and evolutionary history of disciplines [22]. Notably, the current tools used in bibliometric studies include CitNetExplorer, CiteSpace, HistCite, SciMAT, Sci 2, and VOSviewer [23]. In this study, CiteSpace was employed owing to its simple operation and multiple advantageous features, including the generation of mutation-detection algorithms and time-trend graphs based on time changes, trend prediction, and the exploration of more mutational hotspots [24].

To date, bibliometrics has been widely used. For instance, Koseoglu et al. [25] investigated the current status of tourism research based on tourism and hospitality journals; Dabbagh et al. [26] investigated the development trend and current status of blockchain research papers and identified the latest achievements and challenges in the blockchain technology. Basilio et al. [27] explored and summarized the research conducted on various aspects of domestic violence over the past five decades based on bibliometric analysis, providing new ideas for future research. By rationally utilizing bibliometrics, Zhang et al. [28] systematically analyzed the research status, development process, and potential trends of sustainable urbanization. Following this, key issues in sustainable urbanization, including the rational control of urban expansion speed, effective coordination of urban and rural development, the formulation of evidence-based urban development strategies, and guaranteeing urban residents' living standards, are expected to become more critical compared with other research directions in the future. In the field of police affairs, researchers have analyzed several police strategies and related theme papers from 58 countries over the past 50 years through bibliometric methods, providing directions for future research in this field [29]. In education, Jia et al. [11] analyzed the AI trends and related applications in online learning and identified that AI-assisted learning has recently emerged as a popular topic. By performing a systematic review and bibliometric analysis in the field of information science, Kong et al. [30] summarized numerous studies on the urban environment, society, and sustainability using big data. They concluded that human behavior contributes to the most typically used big data in urban environments. Analytical methods can be classified into five primary types: Classification, clustering, regression, correlation rules, and social-network analysis. Overall, most previous studies have employed bibliometrics to investigate the development trends of research fields and recommend relevant research improvements.

3. Dataset and Research Methodology

3.1. Dataset

Note that all papers used in this study were collected from the Web of Science (WOS) (database) [31], which is used in more than 200 disciplines. The major sources used in the database are the SCI expanded and the social science citation index. A search query TS = ((“Machine learning”) and (“Neurorobotics” or “robotics”)) was created to achieve the goal of this study. The retrieval period was set from 2013 to 31 December 2021. The literature was classified as “articles”, and the category in the WOS database was chosen as robotics. In total, 158 papers were retrieved from the database based on the approach described above. It should be noted that, in this study, we conducted bibliometric data analysis on data collected since 2013, primarily because most bibliometric methods adopt a time period as the scope of their search. For example, a period of more than 5 years can be regarded as the scope of a search. To ensure the rationality of data collection and reduce deviations and errors in time selection [24], we considered the period from 2013 to 2021 as the scope of the search in our study. We used the WOS database because it contains the primary literature from SCI and social sciences citation index journals, and most countries and researchers view it as a source of literature published in core journals. In addition, other databases, such as SCOPUS and Science Direct, were not employed in this study because most of them store papers from seminars or non-English papers, which can lead to deviations and errors in the data analysis [11,14].

However, after several rounds of screening, certain issues still prevailed. For instance, some keywords in certain papers only briefly described the context of their study and were unrelated to the study. Instead of being directly related to the research, the theme and keywords were merely explanations of certain terms in the paper. Therefore, data cleaning was necessary for all the selected 158 papers, which required manual analysis tools. Notably, some of the keywords could not be used without data cleaning. To address these problems and ensure a strong association between the data and analysis, we adopted the research technique considered by Wang and Ngai [32], and three researchers scrutinized the abstracts of all 158 papers. After manual screening, papers that conformed to the study theme were retained for further processing, whereas those that were irrelevant were excluded. Consequently, 46 articles were found to be consistent with the theme of this study, and the remaining 112 were excluded owing to insufficient references to neurorobotics (see Figure 1).

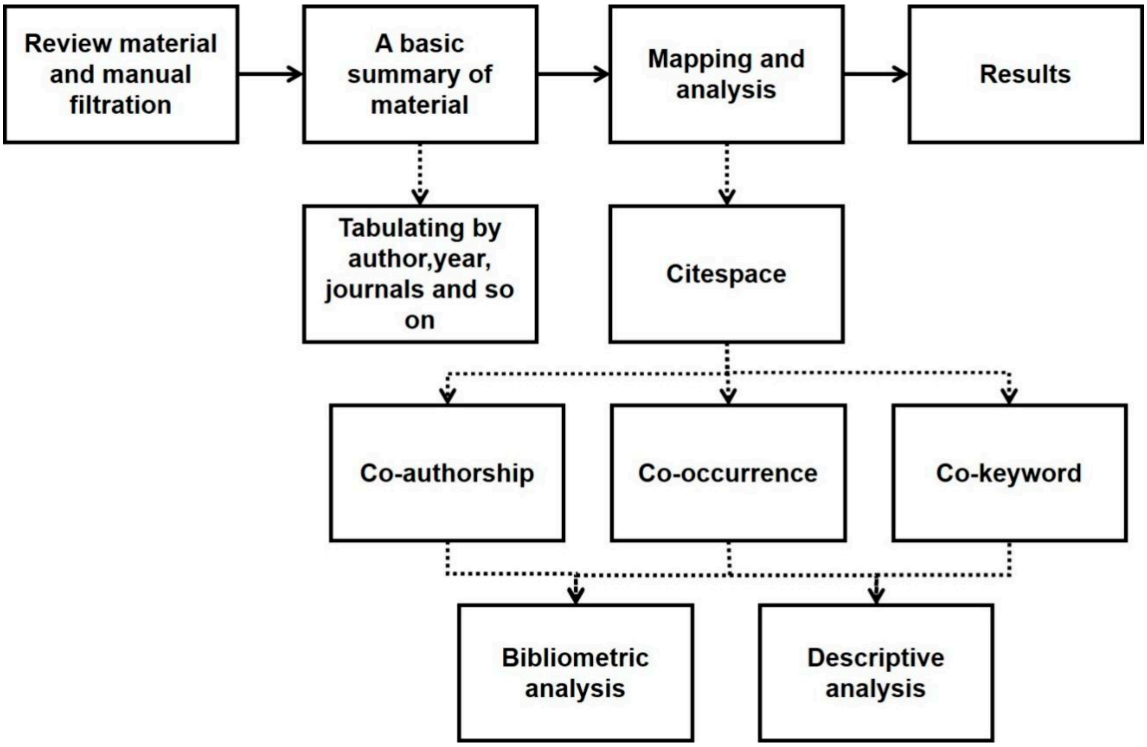

Figure 1. Process framework.

3.2. *Research Methodology*

3.2.1. Keyword Network Construction

Keyword networks are often utilized to analyze research topics and hotspots in various disciplines [33,34]. They were first proposed by Callon, Courtial, Turner, and Bauin [35] and are used to analyze the evolution characteristics of knowledge structures in research fields. The underlying principle involves document collection from cleaned documents:

P = {$P1$, $P2$, . . . , Pn}. Simultaneously, a keyword set of a single document is generated for the keywords appearing in each document in the document set P: K (P) = {$KP1$, $KP2$, . . . , KPn}; that is, the keyword set of each document holds all the keywords related to the literature. On this basis, according to the correspondence between the documents in sets P and K (P), a "document–keyword" membership matrix is constructed. This matrix is a binary rectangular matrix. Using frequency weighting, the binary "document–keyword" membership matrix is further converted into a multi-valued "keyword–keyword" adjacency matrix (square matrix). Because the considered research focuses more on the relationship between keywords rather than their frequency, the "frequency" in the conversion process refers to the frequency of the co-occurrence of two keywords and not the frequency of the occurrence of a single keyword. For instance, if the keywords Ki and Kj appear in a particular article, the relation weight is recorded as one, and if the two keywords appear together in n articles, the relation weight is recorded as n. Finally, according to the constructed "keyword–keyword" multi-value adjacency matrix, a knowledge network G (K, R, W) is constructed, where K denotes the set of knowledge nodes in the network (K = {K1, K2, . . . , Kn}), R denotes the set of associations between knowledge nodes (R = {R1, R2, . . . , Rm}), W denotes the connection, and A denotes the collection of weights (frequency of associations) (see Figure 2).

$$M_{PK} = \begin{bmatrix} PK_{11} & PK_{12} & \cdots & PK_{1n} \\ PK_{21} & PK_{22} & \cdots & PK_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ PK_{m1} & PK_{m2} & \cdots & PK_{mn} \end{bmatrix} \xRightarrow[\textit{Matrix conversion}]{} M_{KK} = \begin{bmatrix} KK_{11} & KK_{12} & \cdots & KK_{1n} \\ KK_{21} & KK_{22} & \cdots & KK_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ KK_{n1} & KK_{n2} & \cdots & KK_{nn} \end{bmatrix}$$

Figure 2. Matrix transformation.

3.2.2. Knowledge Community Division

In any subject area, the relationship between various knowledge communities is not completely random and independent; instead, a certain knowledge community structure is formed by the closeness of association between such knowledge communities. Notably, knowledge nodes in a knowledge community are closely related and form specific knowledge topics. Newman et al. [36] proposed a modularity algorithm to quantify the degree of clustering in network knowledge communities. This method could effectively cluster network nodes with different degrees of association and divide the community. Further, Blondel et al. [37] improved the method to dynamically examine the inflow and outflow of knowledge community nodes and the changes in the association between nodes against a background of massive data; this is referred to as the Louvain algorithm in academic circles. The Louvain algorithm is a graph data-based algorithm for community detection. Its optimization goal is to maximize data modularization. The following matrix for the calculation of modularization is shown in Figure 3.

$$\Delta\mathbb{Q} = \left[\frac{\sum_{in} + 2k_{i,in}}{2m} - \left(\frac{\sum_{tot} + k_i}{2m}\right)^2\right] - \left[\frac{\sum_{in}}{2m} - \left(\frac{\sum_{tot}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right]$$

Figure 3. Equation for Louvain method.

Here, we used the Louvain algorithm to identify knowledge communities in the field of robotics and deep learning and consequently use them to characterize the topic clustering of neurorobotics. Accordingly, we discovered that even if the domain knowledge was divided into different knowledge communities through the community discovery algorithm, during the evolution and growth of domain knowledge, numerous relationships with only one frequency could be identified. Such structural relationships inevitably exhibit a certain degree of contingency or randomness, which is not conducive to domain knowledge, topic clustering, and topic evolution analysis. To exclude such contingencies or randomness, we extracted knowledge communities above a certain threshold based on the association frequency and eliminated low-frequency association relationships to make the knowledge community closer and more representative.

4. Results

4.1. Publication Trends

Figure 4 presents the number of articles published annually in the field of neurorobotics from 2013 to 2021. As illustrated in the figure, at least one paper on this topic has been published each year, demonstrating the stable development of neurorobotics. Between 2013 and 2017, fewer than five articles were published each year. In 2018, the number of articles published increased rapidly and reached ten, representing a milestone since the publication of the first neurorobotics paper. From 2019 to 2021, more than five articles were published each year, indicating steady development in the field of neurorobotics.

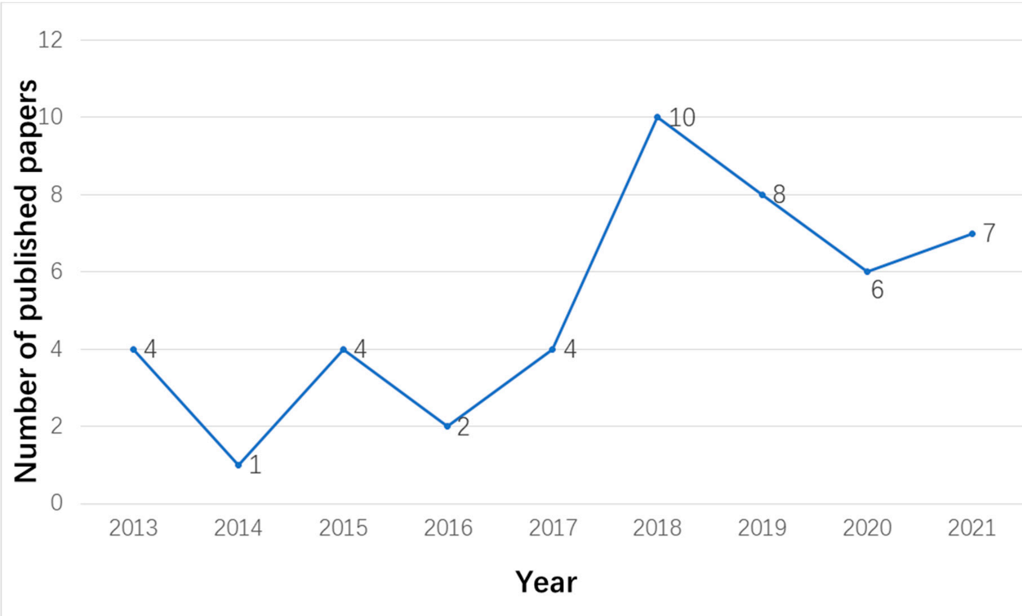

Figure 4. Publications per year.

The number of published articles and citation counts for different journals are listed in Table 1. The Institute of Electrical and Electronics Engineers (IEEE) Robotics and Automation Letters published the most papers (10), with 183 citations. Most of the 10 articles focused on nervous system control based on ML. Frontiers in Neurorobotics published the second most number of papers (seven). Meanwhile, other journals did not publish more than five articles. Notably, Soft Robotics published two articles, with 200 accumulated citations and 100.00 citations per paper on average. Frontiers in Neurorobotics, which published articles pertaining to neurorobotics-integrated ML in 2013, presented the highest number of accumulated citations, that is, 381, with 54.43 citations per paper, on average. Thus, overall, IEEE Robotics and Automation Letters has contributed significantly to the field of neurorobotics in recent years and has published the highest number of articles. Furthermore, it has published articles on neurorobotics annually between 2017 and 2021.

4.2. Authors' Cooperation Network

In terms of collaborations among authors, as depicted in Figure 5, the density of collaborative networks among authors appears low, and the collaboration among authors is insufficient. The authors in the cooperation network are scattered. Egidio Falotico established a close collaboration with Cecilia Laschi. Three of their collaborators, Henrik Hautop Lund, Silvia Tolu, and Marie Claire Capolei, are affiliated with the Technical University of Denmark. Their cooperation was within the scope of the institution. Both Paras Gulati and Farokh Atashzar were affiliated with New York University. Although their collaboration was within the scope of their institution, both cooperated with Qin Hu, who was not affiliated with New York University.

Table 1. Summary of journal publications.

Rank	Journals	Documents	TC	D/TC
1	IEEE Robotics and Automation Letters	10	183	18.30
2	Frontiers in Neurorobotics	7	381	54.43
3	IEEE Transactions on Robotics	4	101	25.25
4	International Journal of Robotics Research	3	155	51.67
5	International Journal of Advanced Robotic Systems	3	54	18.00
6	Soft Robotics	2	200	100.00
7	Autonomous Robots	2	46	23.00
8	International Journal of Social Robotics	1	30	30.00
9	Advanced Robotics	2	18	9.00
10	Science Robotics	1	10	10.00

Figure 5. Author cooperation network from 2013 to 2021 (Documents > 2).

In terms of the number of published articles, Table 2 indicates that nine authors published more than two articles. Among these nine authors, Egidio Falotico published the highest number of papers (five), followed by Cecilia Laschi (three papers and two papers by the remaining authors). Hence, they all published at least two articles.

Table 2. Authors with more than three publications and their number of citations.

Rank	Authors	Count	Year
1	Egidio Falotico	5	2017
2	Cecilia Laschi	3	2017
3	Henrik Hautop Lund	2	2019
4	Qin Hu	2	2021
5	Sylvain Calinon	2	2017
6	Silvia Tolu	2	2019
7	Sfarokh Atashzar	2	2021
8	Paras Gulati	2	2021
9	Marie Claire Capolei	2	2019

In terms of citation counts, three papers were found to have more than 150 citations based on the analysis of the WOS database. The most-cited paper, with 212 citations, was authored by Atzori et al. [38], who investigated the natural control of robotic hands using surface electromyography. Their study was followed by a paper with 185 citations authored by George et al. [39], who analyzed various controllers developed for continuum/soft robots. In their study, the researchers guided future applications of soft robots, comprehensively evaluated different control strategies, and surveyed the prospects of future research in the field of soft robots. In addition, the three most-cited papers were identified (see Table 3).

Table 3. Most-cited publications.

Rank	Author	Title	Citations
1	Zhang et al. [28]	Deep Learning with Convolutional Neural Networks Applied to Electromyography Data: A Resource for the Classification of Movements for Prosthetic Hands	212
2	George et al. [39]	Control Strategies for Soft Robotic Manipulators: A Survey	185
3	Sünderhauf et al. [40]	The limits and Potentials of Deep Learning for Robotics	130
4	Yang et al. [41]	Repeatable Folding Task by Humanoid Robot Worker Using Deep Learning	80
5	Gijsberts et al. [42]	Stable Myoelectric Control of a Hand Prosthesis Using Non-linear Incremental Learning	70

4.3. Countries and Institutions

Further, the cooperation among institutions was found to be limited. Only a few institutions collaborated with others, such as the Scuola Superiore Sant'Anna and the Technical University of Denmark, the DLR-German Aerospace Center, and the Idiap Research Institute. Among these, the first two had a stronger partnership.

In terms of the number of articles published by institutions, as presented in Table 4, eight institutions published more than two articles. Scuola Superiore Sant'Anna published the highest number of articles (six), whereas the other institutions published two.

Table 4. Institutions that published more than two articles.

Rank	Institutions	Count	Year
1	Scuola Superiore Sant'Anna	6	2017
2	University of Bristol	2	2019
3	Technical University of Denmark	2	2019
4	Idiap Research Institute	2	2017
5	The University of Sydney	2	2013
6	New York University	2	2021
7	Bielefeld University	2	2019
8	DLR-German Aerospace Center	2	2014

Further, cooperation among countries is illustrated in Figure 6. As indicated, Germany presents the highest number of collaborations with other countries, followed by Italy. Japan has the fewest partnerships with other countries.

Regarding the number of published articles, 11 countries published more than two articles, with Germany publishing the most articles (10), followed by nine articles from Italy and eight articles from the USA. Although the difference between the number of published articles between all the ranks was only one, Germany published all articles in 2013, whereas Italy and the USA published their articles in 2017 and 2018, respectively.

As illustrated in Figure 6, among the 11 countries, Germany published the most articles and presented the most open collaboration relations with other countries, such as Spain, France, and Italy.

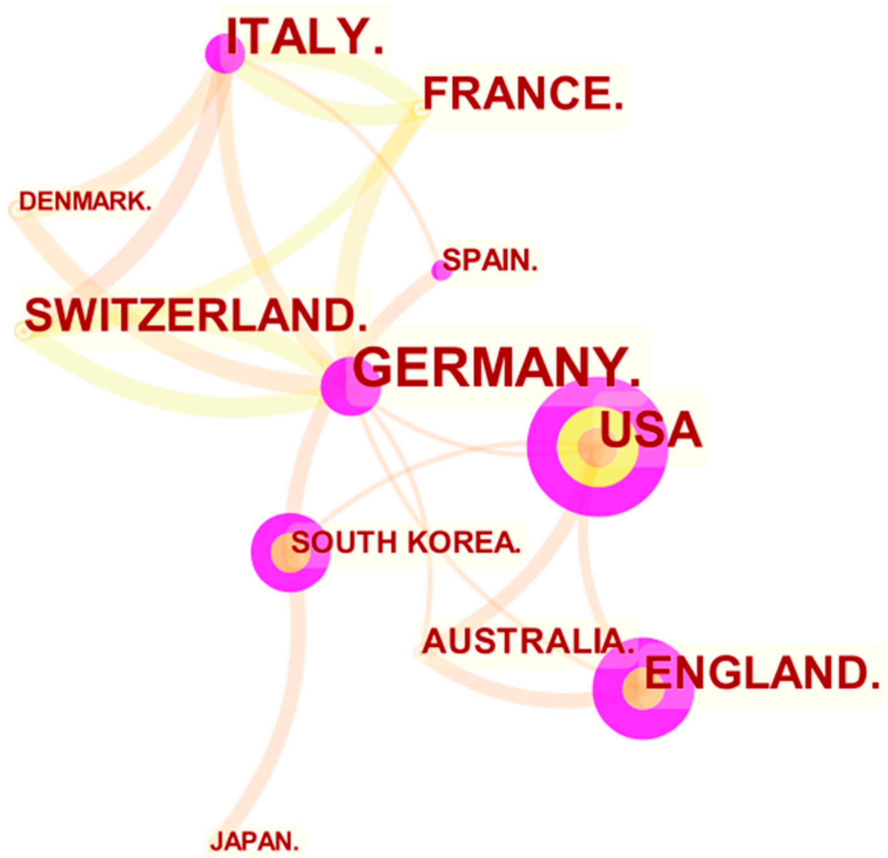

Figure 6. National cooperation network of countries with more than two published articles.

4.4. Keyword Analysis

Notably, a timeline view can provide an overall picture of the timespans of different clusters and the linkages among different clusters, as depicted in Figure 7. The current study involved four clusters, where the nodes in each row represent the keywords of each cluster. The connection lines represent the relationships between different keywords. The connection between points and lines directly reflects the time at which the keyword first emerged in the research field and the relationship among different keywords. Figure 7 indicates that Clusters 0 and 1 contain the greatest number of keywords, which implies their importance; hence, these two topics have received considerable attention. In addition, Clusters 2 and 3 have larger nodes, indicating that they have been intensely focused on.

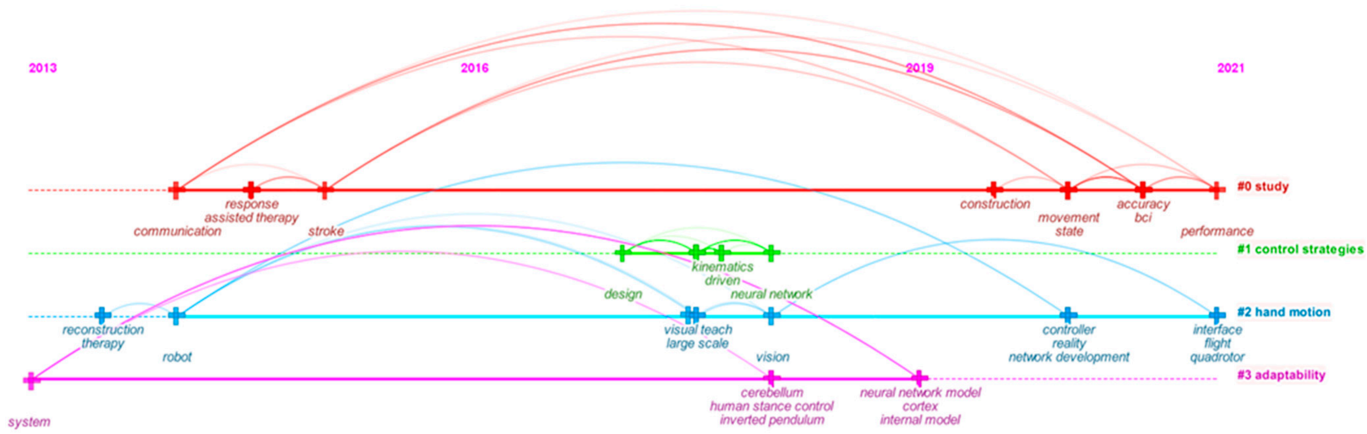

Figure 7. Timeline view of "neurorobotics" cited network.

On the CiteSpace interface, keywords were regarded as nodes, and the time slices were set to one. By using the G-index as the selection criterion, k = 25 was confirmed. After performing our analysis, a co-occurrence atlas of keywords, comprising 173 nodes and a network density of 0.0402, was obtained, as illustrated in Figure 7. Figure 7 lists the nodes, with different colors representing the different clusters (i.e., research topics), showing keyword nodes with frequencies above 2 or equal to 2.

The clustering keyword in Cluster 0 was “study”. The other clustering keywords included movement, stroke, communication, state, performance, accuracy, brain–computer interface (BCI), response, assisted therapy, and construction. This clustering focused on robotic arms and robots. The BCI helped improve the accuracy of robots’ understanding of people’s thoughts and satisfied the requirements of users. Notably, direct human–computer two-way information interactions have significantly benefited society. For example, such interactions can provide assisted therapy (assisted be) to patients prone to strokes to improve the accuracy of navigation systems [31,43,44]. The clustering keyword in Cluster 1 was “control strategies”. The cluster included neural networks, kinematics, driving, and design keywords. To satisfy the demands of various fields more comprehensively, including kinematics, medicine, and business, researchers have prioritized the design and optimization of robotic systems or comparisons between different systems in clustering [32,45,46].

The clustering keyword in Cluster 2 was “hand motion”. Other keywords for clustering included visual teaching, vision, therapy, robot, reconstruction, reality, quadrotor, network development, large-scale, interface, flight, and controller. This clustering involved extensive research on robots. The most significant difference between Clusters 0 and 2 was the direction and intensity of information interaction, with the latter focusing more on robots’ operations and being more consistent with customary human practice. Previously, large-scale experiments in this cluster have been performed, thus endowing humanity with better services through either the active or passive use of controllers [40,47].

The clustering keyword in Cluster 3 was “adaptability”. Other keywords for clustering included system, neural network model, inverted pendulum, internal model, human stance control, cortex, and cerebellum. This clustering not only focused on human–computer interactions while providing more services to humans but also focused on designing robots that closely resembled humans; these include robots that can control themselves similar to human stance control (human stance control; cerebellum) [48,49] and think like human beings via a similar network model (network model) [50–52]. Therefore, the robots used in the clustering process may be more independent.

4.5. Content Analysis of Neurorobotics and Machine Learning

Due to the small amount of literature for analysis, this study aimed to reinforce the current status and content of the research in which bibliometric analysis failed to investigate neurorobotics and ML. To this end, we carried out a literature review through content analysis, and then referred to the studies of Nagariya et al. [53] and Lin et al. [54] to use both bibliometric analysis and content analysis. The purpose of adopting mixed analysis methods is to help reduce the bias associated with traditional interview methods by complementing each other in a holistic, objective, and responsible manner. In terms of content analysis, this study adopted a literature review and analysis. Three professors and two postgraduates were divided into two groups to read the literature, and then the literature was preliminarily sorted and classified by three research members. The accuracy and correctness of the classification were ensured by a review of three professors. Common types of neurorobots are used to study motor control, memory, action selection, and perception. However, due to the small amount of literature involved in this study, the literature was mainly divided into two types: Literature related to applications and literature related to algorithm improvement.

In the concluding section, studies related to algorithms are presented as follows. Sari [55–57] investigated the effect of different learning algorithms on the learning performance of neural networks in inverse kinematic model learning for seven-joint redundancy robots. After implementing various training algorithms, they found that the Levenberg–Marquarth (LM) algorithm was significantly more efficient than other training algorithms. Polic et al. [58] used a new perceptual algorithm in the field of haptic robotics that used a convolutional neural network encoder structure for dimensionality reduction of optical-based haptic sensor image outputs. In addition, Thuruthel et al. [59] proposed a model-based policy learning algorithm for closed-loop predictive control of soft robot manipulators. Jetchev and Toussaint [60] used a new approach to trajectory prediction to demonstrate optimal motion as an appropriate trajectory for fast prediction of new situations, which improved the optimality of the robot motion. Reviewing such studies, the main topic is still algorithm improvement.

Studies related to applications are as follows. Bruno et al. [61] proposed a new strategy for the body learning position controller of the flexible surgical manipulator for minimally invasive surgery. Malekzadeh et al. [62] provided a multi-level architecture from low-level control to high-level motion planning for a bionic handling-assist robot. They deployed all levels of learning to apply learning from demonstration to real-world manipulation tasks. Lippi [49], on the other hand, investigated the application of bionic modules to the control of robotic humanoid poses. Asgher et al. [63] designed a lightweight wearable robotic manipulator for use with a portable fNIRS system to acquire mental workload (MWL) signals to help potential stroke patients through an integrated portable brain interface. These studies reflect neurorobotics at the application level, focusing mainly on applications related to medical use and factory automation.

5. Discussion and Conclusions

5.1. Discussion

Based on bibliometrics and the CiteSpace software, data on neurorobotics collected from the WOS between 2013 to 2021 were scrutinized, and the status and direction of research were discussed. Multiple studies indicated that ML, one of the major research directions in AI, has profound implications for the development of neurorobotics. Below, the conclusions and implications are summarized based on the analysis results.

Most articles on neurorobotics were published by IEEE Robotics and Automation Letters, Frontiers in Neurorobotics, IEEE Transactions on Robotics, the International Journal of Advanced Robotic Systems, and the International Journal of Robotics Research. Among them, only Soft Robotics (100.00), Frontiers in Neurorobotics (39.44), and the International Journal of Robotics Research (33.64) had citation rates of more than 50.00 citations per study. Thus, owing to its high number of publications and high citation rate, Frontiers in Neurorobotics is a leading journal in the field. Meanwhile, although Soft Robotics had a citation rate of 100.00 per study, only two papers were published. Among the studies mentioned above, George et al. [38] presented a specific evaluation analysis of the applications and algorithms of neurorobotic controllers through a comprehensive assessment of future applications and various control strategies in the field of soft robotics, as well as an insight into the future research areas in this field. As far as the trend of research journals' inclusion of ML and neurorobotics is concerned, the relevant calls for papers are still mainly from journals that focus on robotics topics.

As discussed in the analysis of clustering keywords used by users in this field, the following primary clusters were studied: Hand motion, adaptability, and control strategies, which are partly associated with studies on robot exoskeletons [64,65]. For keyword salience analysis, decentralized research was conducted in a disorganized direction before 2016, which is attributable to the early development of neurorobotics. Since 2016, several articles with high citation rates [38–40] have been published, along with a significant number of papers regarding neurorobotics. This publication evolution is attributable to the systematic standardization and comprehensive investigations of problems encountered in the field. In addition, after 2019, most publications in this field focused on systematically and comprehensively investigated topics from 2016 to 2018, such as deep learning for robots and algorithm development for robotic arms. These keyword clusters indicate that deep learning and robot design are the two primary directions in neurorobotics research and are vital to current investigations, particularly those on computer vision. Future research and development of robotic arms should be more efficient, accurate, and beneficial. The research directions in this field are based on similar roadmaps over time, that is, from surface to spot and from superficial to comprehensive investigations, indicating that the theoretical basis and experimental research considered by scholars are maturing with the research directions. Furthermore, developments in other directions should be investigated, and the scope of this study should be improved to enhance the field framework further.

Second, in terms of the current status of institutional and national publications, the most published country is mainly Germany, followed by Italy and the USA. In terms of institutional publications, only a few institutions collaborated with others, such as Scuola Superiore Sant' Anna (Italy), the Technical University of Denmark (Denmark), the DLR-German Aerospace Center (Italy), and Idiap Research Institute (Switzerland). These partnerships are mainly distributed in the European region. The authors of the top two most cited studies, i.e., the studies of Atzori et al. [38] and George et al. [38], are concentrated in this region. This shows that the international and institutional collaboration in neurorobotics is not deep, and only some of the research institutions have strong partnerships.

Third, neurorobotics research mainly focuses on medical-related topics (e.g., [61,63,66,67], but there is also research on neurorobotics for algorithm improvement [59] and enterprise automation [41,62]. Overall, neurorobotics research is still mainly biased toward medical-related fields, and researchers can subsequently explore or expand the applications of these fields in more depth.

5.2. Implications for Academic Research

Neurorobotics is the branch of neuroscience and robotics that deals with the study and application of the science and technology of embodied autonomous neural systems such as brain-inspired algorithms. Therefore, in contrast to simulated environments, most neurorobots need to operate in the real world. Through bibliometric coupling, keyword emergence, and manual reading of research articles, including collating research methods with the use of neuroscience tools, this study presents the following promising topics to future researchers for further discussion.

First, it can be found from the previous research that the research of neurorobotics and ML focuses on the design and optimization of the robotics system and comparison between different systems. When it comes to either business- or medical-related issues, especially the lack of medical personnel or the lack of workers in business due to the disease diagnosis in the post-2020 COVID-19 epidemic, future studies can more thoroughly investigate how to efficiently combine neurorobotics and ML to effectively reduce the economic downtime and manpower loss caused by the epidemic.

Second, there are also many topics related to algorithms or practical applications in the research of neurorobotics and ML. Similarly, when it comes to optimization problems such as logistics transportation, especially how to reduce the consumption in the process of human transportation and to effectively improve the efficiency of enterprise operations, such research provides a perspective for subsequent reflection or research on the application of neurorobotics and ML.

Finally, at the intersection of many fields of AI, neuromorphic systems, and other forms of bionics, a long-standing unanswered question concerns how AI systems should mimic the norms for natural phenomena of learning and adaptation, and what the construction of such structures is. These also require improvements in more diverse algorithms to narrow the fallout between runs on neurorobotics, thereby improving the scope of tests and experiments that can be performed in neural process research.

5.3. Research Limitation

This study, however, has certain limitations owing to the insufficient amount of data involved and the qualitatively presented keyword nodes in CiteSpace. From a quantitative perspective, the value represented by a node is derived from the number of occurrences of that keyword in the entire bibliometric dataset. This study would have been more convincing if the software had weighted the number of occurrences of the keyword and the authors' publication order in the specific literature. Second, a bibliometric analysis of the existing literature was conducted. The bibliometric analysis mainly ranked only paper keywords, authors, journal names, and country network relationships. In this case, only 46 SCI papers were analyzed in this study. Such a small amount of literature is also a limitation of this study. Especially, the data analysis was conducted using SCI journals as the main source of data, but the research on neurorobotics is not only included in SCI journals, but also in many Engineering Index (EI) databases. This is another limitation of this study. Third, this study used Citespace to conduct a broad survey of specific research areas. However, the analysis of the knowledge mapping only discussed the relevance of the broad literature without considering the trends of individual studies or topics. In addition, the content analysis only presented the discussion from the perspective of the data without refining specific topics or articles for in-depth analysis. Therefore, future research could also consider combining Citespace with other software for a more in-depth analysis of articles in the field of neurorobotics combined with ML.

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