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CHARTING THE RESEARCH TERRAIN OF INTENTION RECOGNITION THROUGH CITESPACE ANALYSIS

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Abstract: Intention recognition (IR) plays a vital role in various domains like human-robot interaction, human-computer interaction, and human-vehicle interaction. It is crucial for enhancing the efficiency of human-robot collaboration, as seen in the application of rehabilitation robots. Researchers leverage Electromyography (EMG) to capture lower limb neural information, reflecting human intentions. Hidden Markov Models (HMM) have been employed to predict these intentions. Machine learning algorithms, including attention-based Long Short-Term Memory (LSTM) Networks, Convolutional Neural Networks, and Herman Neural Networks, are used to classify intentions accurately. Recent advancements in sensor technology have improved human motion recognition and the monitoring of muscular activity. This has led to a substantial growth in the literature related to IR. To facilitate a comprehensive understanding of this research landscape, tools like CiteSpace are employed to create knowledge maps, highlighting research trends and frequently used methods.

Keywords: Intention recognition, Electromyography, Hidden Markov Model, Machine learning, Sensor technology, CiteSpace.

Introduction

As Intention recognition (IR) is a major area of interest within many areas of interaction, such as human-robot interaction [1], human-computer interaction [2] and human-vehicle interaction [2]. For example, many rehabilitation robots [3] are used to interact with human to increase the effectiveness of their assistance. As a result, IR is important for a wide range of research directions, including computer science, mathematics, engineering and robotics [4]. In many researches, Electromyography (EMG)[5] has been proposed as a signal to acquire a lower limb neural information which presents the intention of participants. Some scientists have applied Hidden Markov Model (HMM) [7] to predict human intention. As machine learning can accurately classify intentions [8] with data provided, many related algorithms such as attention-based Long Short-Term Memory (LSTM) Network [8], and Convolutional Neural Network and Herman Neural Network (CNN-ENN)[10] have been applied into IR. Furthermore, sensors are well developed recently to recognize human motions [10], the information about human muscles [5] or movements of other vehicles [11]. Recently, a considerable amount of literature has grown up around the theme of IR. Therefore, it is demanding for scholars to quickly and accurately analyze the current state of research on IR at multiple levels and to quickly find research hotspots among such many references. With the help of CiteSpace, hot research topics, as well as frequently used methods, can be presented as knowledge maps.

Knowledge map has been proved to be an effective and convenient method to organize and visualize numerous knowledge and we can use some software to make them. HistCite[12], RefViz[13], DIVA[14], VOS Viewer[15], CiteSpace[16] are commonly used by researchers in bibliometric researches. Compared with other softwares, CiteSpace has some advantages in visualization. It has several main concepts [17]: heterogeneous networks, centrality, betweenness, and burst identification. These concepts mainly applied in three aspects [18]: categorizing keywords, recognizing the feature of research frontiers, identifying burst changes.

Several reviews about intention recognition have been published, and they focus on EMG signals [19],[20],[21], and neural networks[22]. However, these reviews have not conducted detailed studies with statistical data of articles. In addition, there have not been knowledge structures of IR to survey current issues and hotspots. This paper will use CiteSpace to conduct a visual overview of the papers in web of science related to IR for the past 11 years, by visualizing various networks, such as cocited references, keyword clusters, highly cited authors, and hotspot fronts. From these results we can identify the current frontiers and indicate the future research directions.

1. Data extraction and methodology

2.1. Data extraction

Web of science [23] is known as the largest comprehensive academic research information resource website in the world. Therefore, it is thought to be an appropriate paper source to conduct bibliometric analysis and draw knowledge map [24]. This study used resources from Web of science core collection (WOSCC) database. Using "intention recognition", "intention identification" or "motion recognition" as the keyword and the various parts of speech of synonyms are linked by OR logic. The English language filter were used. The time span is from 2011 January to 2021 December. After removing irrelevant articles by reading titles and abstracts, a total of 1234 references were retrieved. The recorded data include titles, authors, references and other fully recorded information.

2.2. Research methods

This paper uses CiteSpace (5.8.R3 64-bit) to conduct the visualization study on the countries, institutions, author networks, hot keywords. The literature data collected in the WOSCC are imported into CiteSpace software and various parameters are set. Time slicing is from 2011 to 2012, 1 year per slice. Selecting “Title”, “Abstract”, “Author Keywords”, “Keywords Plus” options under Term source. In order to realize different analysis, choosing corresponding node type in the Node Types option box, such as institution, Cited Author, Keyword. The path finder and pruning sliced networks are selected in the co-author and reference networks. Finally, through the co-occurrence maps generated in CiteSpace, the research hotspots and development relationships are analyzed.

3. Results and analysis

3.1. Annual Publication and Citation Trend analysis

The number of annual publications generally represents the degree of attention in a field. Therefore, we have counted the annual number of publications related to IR from 2011 to 2021 to spot its trend, and the result is shown in Figure 1. The number of publications has increased continuously from 40 to nearly 200 during this 11-years period, and jumped from 95 in 2016 to 141 in 2017. This may be due to the AlphaGo of Google defeating the world chess champion in a chess game, meaning the intelligent algorithms have arrived at a new stage, which gives researchers the confidence and an incentive to use these useful methods in IR. This rapidly rising trend of publication volumes, robots and other intelligent machines shows a promising future in IR.

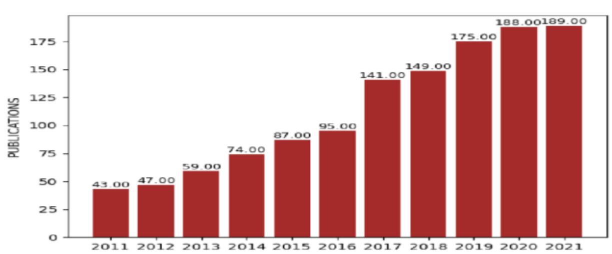

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Figure 1: Annual publication volume.

3.2. Co-author's country, institution and grant analysis

The information of co-authors includes their country, institution and funding. This information is helpful to present the distribution of authors, resources of their funding, then identify the key countries and institutions.

A total of 76 countries in our records are used to identify the influential countries in IR, analyzing their cooperation situations and presenting in Figure 2. The nodes in it represent different countries and the size of a country's node represents the country's publications. The lines represent the correlations between two countries or regions, with thicker lines presenting the stronger connections. The color of of lines reflects the time of cooperation. As shown in Figure 2, 11 countries are shown as well as the connections between them. The number of publications in China and USA is obviously larger than other countries or regions, followed by the numbers of England, South Korea and Japan, et al. China, USA and England have various collaborations with other countries in this field. England is strongly connected with Italy. India, Canada and Germany also have close cooperation.

Figure 3 illustrates the most productive institutions in our recorded 1283 institutions. These institutions mainly distribute in China and USA. In USA, MIT is the leading institution and has connections with many other institutions, since the cluster around MIT is tight and obvious. In Table 1, eight of these top ten research institutions are in China. Chinese Academic Science and Tsinghua University are the major agencies in China, followed by Harbin Institution of Technology and Peking University. The cooperation situations are also reflected by the centrality[25], which measures the proportion of one vertex on the shortest path between other vertices. High centrality generally means it is more significant in consideration of the whole studying field. Chinese Academic Science has the highest centrality, indicating it strongly connected with other institutions. In addition, the centrality is in proportion to the number of publications, showing that the cooperation is important during conducting research.

Table 1: Top 10 most productive institutions.

Institution	counts	Proportion	Centrality	Country
Chinese Academy of Science	114	6.075	0.19	China
Tsinghua University	28	2.238	0.09	China
Harbin Institution of Technology	27	2.158	0.05	China
Peking University	22	1.759	0.05	China
Northwestern University	21	1.679	0.03	USA
Changan University	22	1.637	0.03	China
Beijing Institution of Technology	17	1.359	0.03	China
MIT	11	0.879	0.02	USA
Sun Yat Sen University	10	0.799	0.02	China

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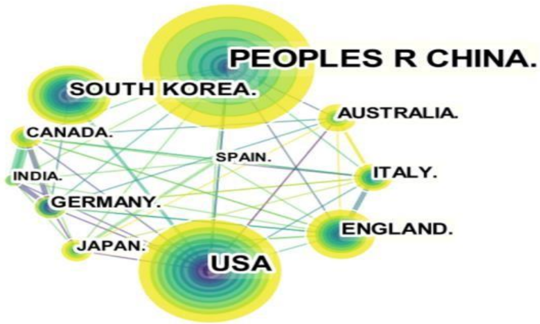

Figure 2: Visualization network map of the country analysis.

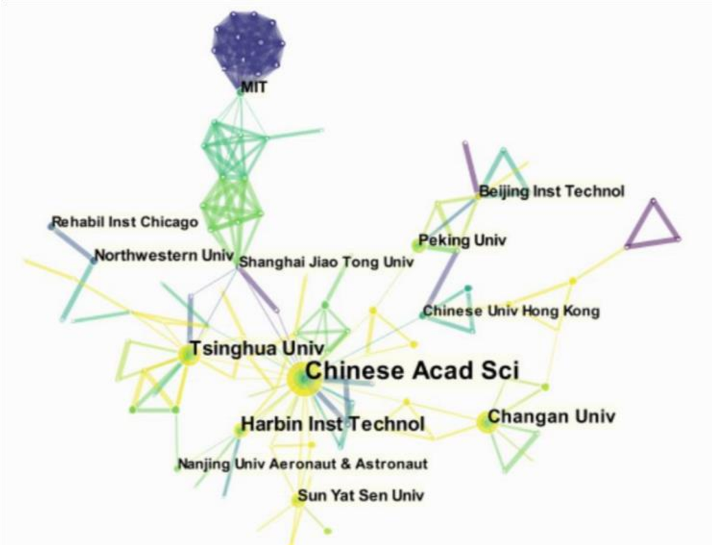

Figure 3: Visualization network map of the institution analysis.

The grant results are visualized in Figure 4. All these foundations belong to China. This may because artificial intelligence has written into several development plans in China, and IR is a field in relation with artificial intelligence. It helps researchers to be more productive, making China to be the leading position in the field of IR. Comparison of the findings with the country and institution analysis shows the standing out of China, which confirms that sufficient funds of a particular research field are significant for researchers to be productive.

Figure 4: Network of grant.

3.3. Author co-citation analysis

The number of publications and cited counts represent an author's productiveness. To clarify the characteristics of the most productive authors in the field of IR, the ten most published or cited authors are provided and analyzed.

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Figure 5 shows the cooperation situations between prolific authors. The size of nodes presents the frequency of citations, and the thickness of lines denotes the strength of connections between two authors. The line between two nodes indicates that there is a connections between these two authors.

As shown in Figure 5, the most productive authors are He Huang, Aaron J. Young, Huseyin Atakan Varol. Young has mostly conducted research about making intelligent machines to help amputees, while He Huang, as well as Huseyin Atakan Varol, are devoted in the field of developing prosthetic legs. The exact citation counts can be seen in Table 2, where He Huang, Aaron J. Young and Huseyin Atakan Varol are the top three highly cited authors. Zhang Zhang ranks fourth, who contributes to feature extraction, machine learning, and image recognition. The research direction of Frank C.Sup is similar to that of He Huang and Huseyin Atakan Varol, devoted to gait analysis, biomechanics, and medical robotics. Levi J. Hargrove makes contributions in both bio-medicine and signal processing. In addition, most of these highly cited authors come from USA, indicating USA is also significant in the field of IR.

Table 2 presents the information of ten authors with the most papers. Most productive authors are mainly in China. Kiguchi K published 35 papers from 2011 to 2021 related to medical robotics, electromyography, and motion. Chao Wang and Jie Wang come from Xi'an Jiaotong University, both of whom conduct research on feature extraction. Many productive authors gather in China. Besides, USA and Japan also stand out. Other countries also have some important contributions in this field, such as Thailand, Iran and Singapore.

Table 2: Top 10 authors with the most papers.

Author	Publications	Percentage	Institution	Country
Kiguchi K	35	1.464	Kyushu University	Japan
Chao Wang	23	0.962	Xi’an Jiaotong University	China
Jie Wang	21	0.878	Xi’an Jiaotong University	China
Levi J. Hargrove	20	0.836	Shirley Ryan Ability Lab	USA
Yang Li	20	0.836	Beihang University	China
Yi Liu	20	0.836	Kagawa University	Japan
Wang Hui	20	0.836	Shenzhen Institutes of Advanced Technology	China
Wang Qingnian	20	0.836	Jilin University	China
Guanglin Li	19	0.795	Shenzhen Institutes of Advanced Technology	China
Xiang Zhang	19	0.795	Singapore Management University	Singapore

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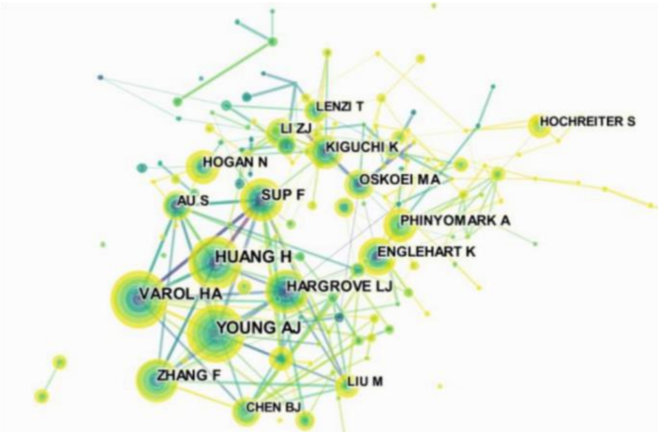

Figure 5: Network of productive authors.

3.4. Journals analysis

The journal citations and publish analysis can provide researchers with some guidance on journal selection. In Figure 6, among 21 nodes, IEEE T NEUR SYS REH and IEEE T BIO-MED ENG are noticeable, which means these two journals are especially important in the field of IR. There are also many connections to both nodes, representing widely co-citation relationships with other journals. Followings are J NEUROENG REHABIL, IEEE INT CONF ROBOT, and IEEE ENG MED BIO. It is worth noting that most of these significant journals are related to bio-medicine.

Table 3 and Table 4 present the top 10 journals with the highest citations or article volume. While many of these articles are under the head of IEEE, there are still some other journals. Sensors is outstanding in both of these two ranks, with 144 citations and 28 publications in total. Furthermore, although many articles in this field are published in journals with an engineering or computer science scope, most highly cited journals aim at biology-medicine or neurology. The uses of bio-related discoveries, resulting in a high number of citations in biology articles, which illustrates the close connection between engineering and biology. Journals with over 200 citation counts are IEEE NEUR T SYS REH and IEEE T BIO-MED ENG. The top five journals among them are all under engineering and computer science.

Table 3: Top 10 journals ranked by citations.

Journal	Citation Counts	scopes
IEEE T NEUR SYS REH	249	the rehabilitative and neural aspects of biomedical engineering
IEEE T BIO-MED ENG	223	biomedical applications; experimental and clinical investigations with engineering contributions.
J NEUROENG REHABIL	147	physical medicine and rehabilitation and human movement augmentation
SENSORS	144	science and technology of sensor and its applications
IEEE-ASME T MECH	138	intelligent mechatronics systems
IEEE T ROBOT	122	all aspects of robotics

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PLOS ONE	103	clinical trial, methods article, protocol, registered report, systematic reviews
ROBOT AUTON SYST	98	fundamental developments in the field of robotics
J NEURAL ENG	97	understand, replace, repair and enhance the nervous system
INT J ROBOT RES	88	robotics and related fields - artificial intelligence,

applied mathematics, computer science, electrical and mechanical engineering

Table 4: Top 10 journals ranked by article volume.

Journal	Publications	Percentage
IEEE ACCESS	35	2.728
SENSORS	28	2.182
LECTURE NOTES IN ARTIFICIAL INTELLIGENCE	27	2.104
LECTURE NOTES IN COMPUTER SCIENCE	26	2.027
IEEE ROBOTICS AND AUTOMATION LETTERS	25	1.949
IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING	25	1.949
BIOMEDICAL SIGNAL PROCESSING AND CONTROL	13	1.013
FRONTIERS IN NEUROROBOTICS	13	1.013
IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING	13	1.013
IEEE INTELLIGENT VEHICLES SYMPOSIUM	9	0.701

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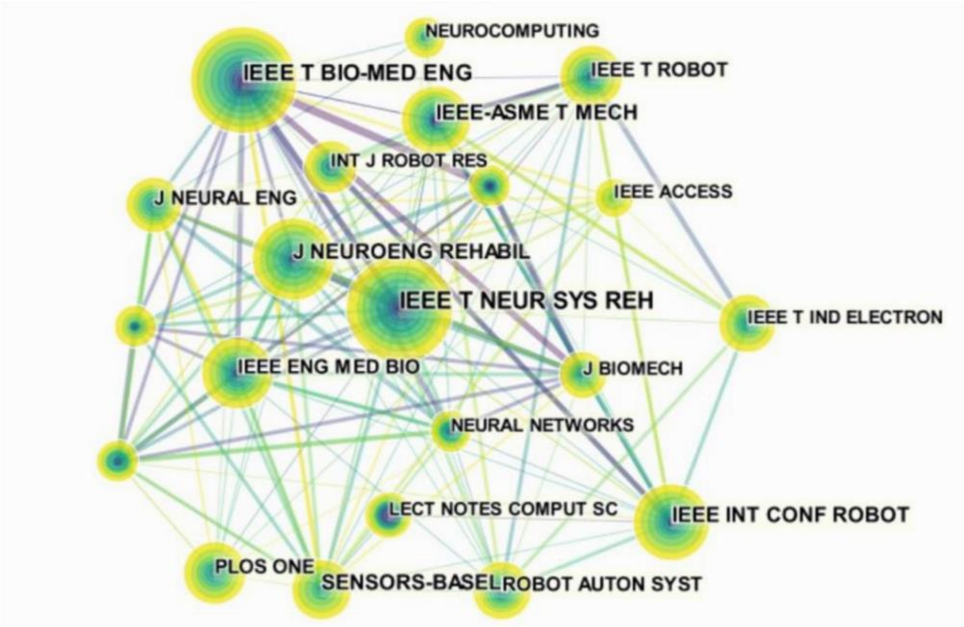

Figure 6: Network of productive authors.

3.5. References analysis

The frequently-cited references and their co-citation relationships can present the basis of a field and research hotspots. From Figure 7, we can conclude that 3 articles owned by Young AJ are frequently cited, followed by the papers of Varol HA, Huang H, and Tucker MR.

Table s1 has summarized 10 references with the highest citation frequencies. In the first paper[26], Young AJ developed a user-independent intent recognition system with the help of a creative modespecific classification system. The following one[27] analyzed several capable intent recognition interfaces, which provided a way of using sensors to get signals and identify intention by processing them. The article by Tucker MR also aimed at creating more helpful prosthetics and orthotics. The following ranked two articles published on IEEE T BIOMED ENG are written by Varol HA and Huang H. The former one[29] which has 18 citations promoted an intent recognition function by gathering timebased information from frames of prosthetic signals to categorize the patterns such as standing, sitting, or walking. It successfully provides a complete process of intention identification. The other article[29] introduced electromyographic (EMG) signals to identify the continuous locomotion-mode's intention. Additionally, the idea of adding time history information for mechanical and EMG sensors into the computation was creative and important for the later studies. The studies of Alahi A and Wakita K are more focused on computers and engineering. Under the influence of Recurrent Neural Network (RNN) models for sequence prediction, Alahi A[30] put forward an LSTM model to predict the future decisions of humans by learning general movements. Wakita K[31] promoted the "intentional direction(ITD)" concept to recognize the walking intention, making the process of designing a motion controller of a cane robot easier. Most of the highly cited articles aim to provide more effective prosthetics, while some of them focus on vehicles and robots. In order to classify the diverse meaning of different signals, researches in this field are commonly combined with engineering, computer algorithms and neurology.

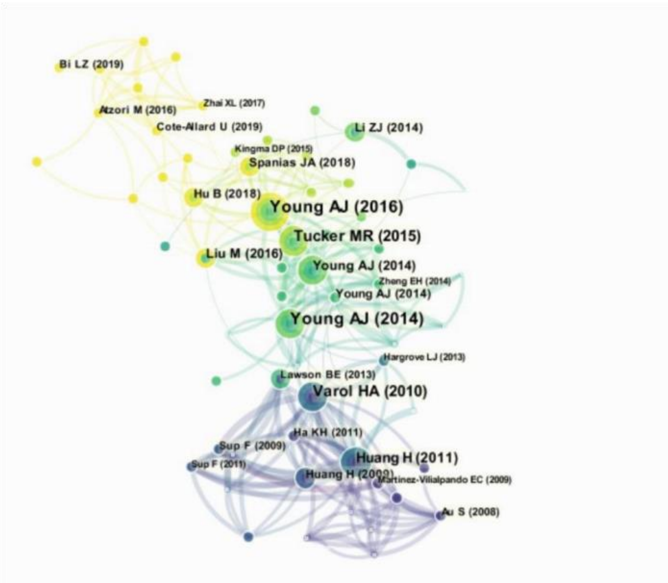

Figure 7: Network of cited references.

3.6. Keywords analysis

Keywords[32] in scientific literature are phrases chosen and generated by the author which are generally considered to summarize and express the core content of a publication. It is therefore appropriate to use keywords to find research hotspots, bursts and key methods. To process a visual map of the keywords clusters, we select Keyword in Node Types. In Figure 8, there are ten colors, and each color represents a cluster. The more dots in one cluster range denotes there are more articles using this keyword. The keywords contained in Cluster 4 and Cluster 8 are related to getting signals about the stage of the aimed person, machine, or environment, indicating that finding and processing motion signals is a research hotspot in the field of IR. The keywords contained in Cluster 5, Cluster 7 and Cluster 9 are prediction or classification models to identify intention with input data. The keywords in Cluster 6 is motion control, which aimed at controlling the machines to complete the instruction or interaction. The above analysis presents that some experiments related to improving prediction methods or neural networks have been carried out, and in-depth researches on motion signals also have brought to fruition.

Table 5 lists the most cited keywords. Except for intention recognition, intent recognition and recognition, the popular keywords include system, design, model, classification, robot, EMG, walking. However, the centrality of these top 20 keywords is not very high, and only classification, EMG, behavior, are over 0.1. This means the connections in different directions are not so strong, but most of them need to identify the behaviors and use these data to classify intentions.

Table 5: Top 20 frequently mentioned keywords.

Keyword	Frequency	Centrality	Keyword	Frequency	Centrality
system	71	0.01	feature extraction	29	0.03
intention recognition	70	0.01	pattern recognition	25	0.05
intent recognition	69	0.02	behavior	23	0.14
design	63	0.02	movement	23	0.06
model	53	0.05	exoskeleton	20	0.09
classification	48	0.1	strategy	19	0.07

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robot	39	0.05	myoelectric control	18	0.04
emg	38	0.12	human-robot interaction	18	0.03
walking	37	0.03	prediction	18	0.02
recognition	33	0.04	machine learning	17	0.03

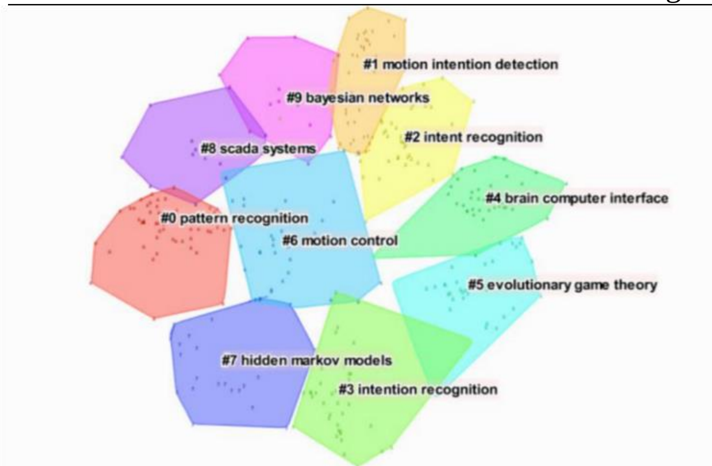

Figure 8: Network of keywords.

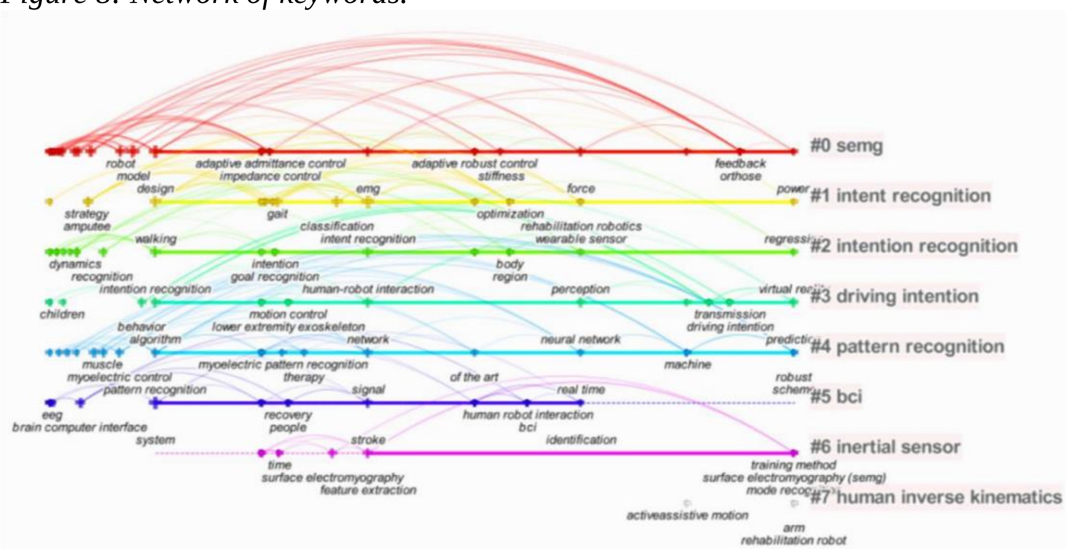

Figure 9: Timeline of keywords.

In Figure 9, we can observe the frequently mentioned keywords in the view of the time zone. From 2011 to 2013, the keywords are more dispersed and universal. With the development in this field, researchers presented more accurate motion signals, a math model (HMM), and specific motion classifications such as walking. Except for intention recognition, there are five keywords clusters. sEMG ranks first and is used most frequently in recent years. EMG is a signal recording the electrical activity of muscles. In recent years, EMG-based recognition methods mainly aimed at processing the informative data. Driving habits differ in terms of temporal and spectral changes in EMG data. Jiawei Ju[33] analyzed differences in the temporal and spectral variation of EMG data for three kinds of driving manoeuvres. Xiangxin Li[34] combined EMG and eye movement signals to fully use their advantages with the SVM classification algorithm which is a machine learning algorithm to identify intention. Various labels in the intent recognition and pattern recognition are related to neural network, such as optimization, neural network and machine. Among the various neural networks, LSTM is the most popular method and has been improved many times. Xue Li [35] proposed a LSTM recurrent neural network which is a non-linear model being used for continuous recognition without segmentation. Xiaoshan Gao[36] mixed the IBiLSTM network and the ILSTM network and put them into different layers to improve the prediction accuracy. In the timeline of driving intention and pattern recognition, both perception and prediction are based on Predictive models, in which HMM is a commonly used method in the field of IR. Researchers also tried the combined models to improve the performance of their method. Xuan Zhao [37] proposed the Gaussian Hybrid Hidden Markov Model (GHMM) the Generalised Growth and Pruned Radial Basis Function Neural Network (GGAP-RBFNN) under this aim. A mixture of HMM and Gaussian mixture models (GMMs)[38] is also an effective method. The clusters ranking at 5th, 6th, 7th are all centralized on amputees and sensors to get signals. Information is more important than algorithm in this direction.

The requirement of real-time will decide how smooth the interaction is, but the recognition time under current neural networks is relatively long. Therefore, in order to improve the interaction experience, quickly identify the user's intention is a challenge in the field of IR. This puts higher requirements for the real time of prediction or classification models.

From the information provided by Figure 8 and Figure 9, three hotspots can be concluded in the field of IR:

(1) Processing signals: The premise of the recognition model is that feature data on our target object or person is already available. Many scientists have focused their attention on accurately acquiring and processing this information and have developed a number of methods including EMG measurements, image processing.

(2) Identification models: This topic, as a vital part of IR draws many researchers' attention. They produced various models and algorithms to conduct classification or prediction. These methods including machine learning, HMM, deep Convolutional Neural Networks, and LSTM have been applied to this topic and are widely employed by many scholars

(3) Multiple uses: IR has various impacts on many fields. Currently, there are mainly three areas mostly influenced. In the bio-medicine field, this technique is commonly used to develop artificial limbs so that owners can use them effortlessly. In terms of vehicles, it can provide instant security signals to drivers or help driverless cars become safer. As for the robots field, these researches will enhance the efficiency and fluency of the human-robot interaction.

3.7. Study frontiers

Table 5 presents the changes of burst keywords during different periods. Before 2013, there is no common keyword in the field of IR, and at that time many methods were tried. It is supposed to be a preparation period for this field. From 2013 to 2015, it can be regarded as a stage, in which three keywords knee, strategy, and perception were bursting out. These keywords are mainly related to biomedicine and are aimed at helping the lame person. The next stage is from 2015 to 2019. During that time, more attention was put into computer science, such as brain-computer interface and human-robot interaction. In recent years, there has been more interest in conducting research into predictive algorithms and models. In addition, feature extraction has been thought highly of because it is usually the prerequisite of classification.

Table 6: Top 14 keywords with the strongest citation bursts.

Keywords	Year	Strength	Begin	End	2011-2021
knee	2011	5.1	2013	2015	
strategy	2011	3.3	2013	2016	

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perception	2011	3.04	2013	2014
amputee	2011	3.66	2015	2018
dynamics	2011	2.55	2015	2018
Brain computer interface	2011	4.98	2016	2018
exoskeleton	2011	4.02	2016	2019
rehabilitation	2011	3.74	2016	2017
Human-robot interaction	2011	2.58	2017	2018
gait	2011	2.88	2018	2021
Feature extraction	2011	6.67	2019	2021
prediction	2011	4.7	2019	2021
algorithm	2011	3.63	2019	2021
Hidden markov model	2011	3.02	2019	2021

In conclusion, two current frontiers can be concluded as follows:

(1) Feature extraction: Extracting features from signals is the first step of IR[34] and is also significant in human motion recognition[39]. A variety of sources of data without processing results in several feature extraction methods requirements, for example, using image processing functions to extract useful information from pictures, separation method to process surface sEMG signals.

(2) Prediction methods: As many researches have successfully completed classification models in the early years, the focus of study has now been shifted to prediction the possible intention of a movement to identify the intention more efficiently. Automatic emergency braking systems[40] can become safer with the help of pedestrian route forecasts. Another direction is for human-robot collaboration[36], since it necessitates the robot's active and intelligent identification of the human operator's purpose. At the same time, a prediction math method HMM is widely used.

4. Research deficiencies and improvement method

4.1. Research deficiencies

Recent algorithms have some deficiencies that affect their robustness and accuracy. Traditional math model HMM has difficulty with capturing long-term trends, some features such as repeated intentions at a specific time of day. Using neural networks need a quantity of labeled data, therefore consuming too much time and energy. In addition, neural network based methods are not very interpretative, making it hard to understand the mechanism of recognition process.

The limitations of EMG signals also limit the accuracy improvements. EMG signals are widely used to reflect the intention of users, but the time-varying feature of EMG[41] making the network easy to become overfitting. EMG signals only represents the movements of muscle. Intentions that not reflect in muscle, such as eye-movements, are not able to identify only using EMG signals. More kinds of signals related to motion intention are waiting to be discovered.

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4.2. Improved methods

For the deficiencies in HMM, some combined method are proposed. LSTM-HMM mixed HMM with LSTM network, making the model be able to recognize both short and long time intention. Some unsupervised methods are proposed to cope with the the demand for a large number of training samples. Stuart Synakowski[42] used an unsupervised model and achieved high recognition accuracy.

Eye movements is also a signal to recognize intention. Many researchers also introduce Electroencephalogram(EEG) into intention recognition. These signals enriched data resources for identifying models.

5. Conclusion

This paper has analyzed 1234 papers in the field of IR from 2011 to 2021 with the assistance of CiteSpace. Visualized knowledge maps indicate that China is the country with the largest number of articles and funds in the field of IR, closely followed by USA. Many other countries also contribute a lot, including England, Italy, Canada, South Korea, Australia, Japan. In these areas, Huang H, Young AJ, and Varol Ha have been regarded as the most productive and influencing researchers. Journal analysis reveals that IEEE T NEUR SYS REH and SENSORS are significant journals in IR. Processing signals, identification models, multiple uses are the research hotspots. It is possible that feature extraction and prediction methods are the frontiers in the future.

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