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1991 to 2019: THE RISE OF MACHINE INTERPRETING RESEARCH

De 1991 a 2019: A EVOLUÇÃO DA INVESTIGAÇÃO SOBRE INTERPRETAÇÃO AUTOMÁTICA

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Conceived as a scientometric study, this paper searches for understanding the research status of machine interpreting on the IEEE (Institute of Electrical and Electronics Engineers) database from 1991 to 2019. Documents were analyzed considering a series of measures such as most prominent academic institutions and countries that investigate machine interpreting, citation, co-authorship, keywords co-occurrence, reference coupling, and textual-based analysis retrieved from the documents' titles and abstracts. Through VOSviewer software and its tools for data collecting and visualization, machine interpreting research in the analyzed *corpus* focuses on three main concerns: machine translation, speech synthesis, and Japanese language.

Keywords: Machine Interpreting. Translation and Interpreting Technologies. Scientometrics.

Concebido como um estudo cienciométrico, este artigo procura compreender o estado da investigação sobre interpretação automática na base de dados IEEE de 1991 a 2019. Os documentos foram analisados considerando uma série de medições como as instituições e países mais proeminentes que investigam a interpretação automática, citação, co-autoria, co-ocorrência de palavras-chave, acoplamento bibliográfico e análise baseada em textos recuperados dos títulos e resumos dos documentos. Através do software VOSviewer e de suas ferramentas de coleta e visualização de dados, a pesquisa sobre interpretação automática no *corpus* analisado centra-se em três aspectos principais: tecnologias de tradução automática, síntese de voz e língua japonesa.

Palavras-chave: Interpretação Automática. Tecnologias da Tradução e Interpretação. Cientometria.

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1. Introduction

Thanks to the high processing capacity of today's computers and mobile devices, and fast and accessible network connections, machine interpreting (MI) apps have been increasingly present in the lives of diverse users around the world. In 2015, a report by Ericsson research agency estimated that 70% of the world's population would be using smartphones by 2020, and 90% of those devices would be covered by mobile bandwidth data networks (Ericsson, 2015). In June 2019, the same agency predicted that, by the end of 2024, the 5G mobile connections will cover up to 65% of the global population, and 35% of global data traffic will be carried over 5G networks (Ericsson, 2019).

In the wake of these developments, MI systems have been spreading around the globe. Such systems merge automatic speech recognition (ASR), machine translation (MT) and text-to-speech (TTS) technologies (Waibel & Fügen, 2008). Amongst these three technologies, ASR has come to the fore in recent years. Virtual assistants such as Amazon's Alexa, Microsoft's Cortana and Apple's Siri, with which users interact through automatic voice recognition, are already part of the routine of millions of people (Sciforce, 2018).

The facts that MI systems are getting better because they are making use of all modern ASR, MT and TTS technologies (Lee, 2015), and the more they are online and freely accessible to a wide range of users the better they get, are attracting the attention of researchers within Translation and Interpreting Studies. It also calls the attention of other knowledge fields such as Computer Engineering and Computational Linguistics. One way to follow MI developments and researchers' efforts in studying this technology is through scientometrics.

Scientometrics analyses, which involve the use of statistical methods, is increasingly being used for research measurements (Doorslaer & Gambier, 2015; Gile, 2015; Zhang *et al*., 2015). Methods used in scientometrics analyses are mainly quantitative, but they can be used to assess the quality of research productivity for a particular country or institution, distinguishing it from other statistical methods applied in bibliometrics, informetrics, webmetrics, cybermetrics, or altmetrics (Tague-Sutcliffe, 1992; Macías-Chapula, 2001; Vanti, 2002; Araújo & Alvarenga, 2011; Lopes *et al.*, 2012).

Quantity itself, however, is at the same time precise and approximate, as it is based on a particular database, which not always will appropriately respond to all scientometric software, techniques and time. Nevertheless, as described by Doorslaer and Gambier (2015), regardless of the sources and materials they investigate, scientometric studies have a descriptive power, and seek to measure the influence of academic centers and their intellectuals,

> When producing and transmitting scientific knowledge, authors weave a web of affinities: they cite some works to the detriment of others; they refer to certain publications; they set up more or less regular intellectual relationships. Nowadays, Translation (and Interpreting) Studies (TS) has the tools (journals, book series, bibliographies, encyclopedias, handbooks, readers, textbooks, etc.) which can trace and visualize outstanding developments in

> research and the most influential authors and centers so far. (Doorslaer & Gambier, 2015, p. 305)

Conceived as a scientometric study, this paper searches for understanding the research status of machine interpreting. Despite the existing important Translation and Interpreting Studies databases such as BITRA (Bibliography of Interpreting and Translation), and TSB (Translation Studies Bibliography), or even general databases available nowadays such as Google Scholar, Microsoft Academic, CrossRef, Scopus, Web of Science, amongst others, the IEEE database was chosen for this study.

The *IEEE Xplore* digital library offers access to scientific content published by the U.S. Institute of Electrical and Electronics Engineers (IEEE) and its partners. According to information retrieved from its website, this digital library holds more than five million scientific papers from the most cited publications of Electrical Engineering, Computer Science and Electronics. Apart from its robustness of resources for scientometric analysis, this database can be freely accessed through the internet network of Universidade Federal de Uberlândia, located in Minas Gerais State, Brazil, the academic institution to which we are affiliated.

This paper presents a scientometric study on MI based on 137 papers retrieved from the *IEEE Xplore* online database, covering the period from 1991 to 2019. The analysis reveals the top institutions and authors involved in MI research, with their co-authorship networks. Moreover, keywords co-occurrence, bibliographic coupling and most relevant terms retrieved from titles and abstracts of the 137 papers reveal important relations amongst these studies on MI.

2. Addressing methodological procedures

All the scientific studies, including conference papers and journal articles, hereafter generally referred to as *papers*, were collected from IEEE Xplore, an online database that allows access to more than five million scientific studies related to Electrical Engineering, Computer Science and Electronics. Papers are in both HTML and PDF formats.

The keyword applied for data collection was *speech-to-speech translation*, a term by which MI is widely identified in English (Freitas & Esqueda, 2017). *IEEE Xplore* advanced search engine generated a report with 163 papers from different types of publications. Out of 163, 26 papers did not provide complete data with keywords and references, and were therefore excluded from the *corpus*. Thus,137 papers were collected from the database, which retrieved them from the period between 1991 and 2019.

2.1 Analyses of the scientometric information

Using VOSviewer, an open source software tool for constructing and visualizing scientometric networks (Eck & Waltman, 2009)[1], we drew maps for the following categories:

[1] https://www.vosviewer.com/

1. Co-authorship: the repeated presence of two or more authors or organizations in a given number of papers (Glänzel & Schubert, 2004);
2. Co-occurrence of keywords: the relationship between keywords and the number of papers in which they co-occur;
3. Bibliographic coupling: the relationship between two papers based on the number of common references cited by them (Grácio, 2016); and
4. Most relevant terms present in the titles and abstracts of the papers.

3. Results and discussions

A graph containing the number of published papers per year, a list of the main publishing sources, the authors with the highest number of publications, the most cited papers and the number of authors per paper is also shown. In the second part, the results of five scientometric and network analyses are shown: co-authorship, co-occurrence of keywords, bibliographic coupling and co-occurrence of terms in titles and abstracts.

3.1 General bibliographic analyses

The dataset consists of 137 papers on MI. They were written by 433 authors and published in 25 proceedings of scientific events and nine journals. The authors are affiliated to institutions from 25 countries of four continents. The papers show a total of 2,282 references, and 2,576 prominent terms are included in their titles and abstracts.

Table 1 shows the top ten countries involved in MI research. The first column contains the name of the country, the second column provides the number of published papers, and the third column provides their percentage. The sum of the percentages exceeds 100% because the great majority of papers report studies funded by more than one country.

Table 1. Top 10 countries involved in MI research.

Country/territory	Number of papers	% of 137
USA	64	46,71
Japan	32	23,35
Germany	22	16,05
India	10	7,29
China	9	6,56
France	7	5,10
Spain	5	3,64
Italy	4	2,91
Egypt	3	2,18
United Kingdom	3	2,18

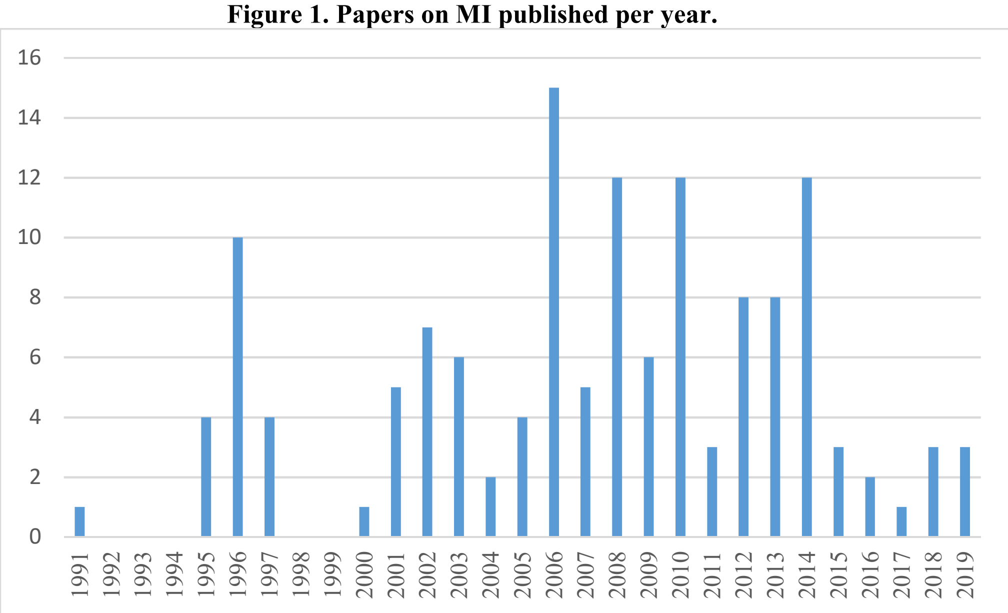
USA researchers are the most productive during the period of 1991 to 2019. Due to the fact that the great majority of papers on MI shows collaborations amongst researchers from several countries, the data indicate that 46.71% of the research on MI were published by at least one researcher from the USA. Japan is the second most productive nation, contributing with 32 papers (23.35%). Other productive countries are Germany (22), India (10), and China (9).

The contribution of these five countries, when taken together, amounts to 100% of the publications on MI in the last two decades, leaving no doubt that researchers from these countries are playing a leading role in MI research. Except for Japan, China, India and Egypt, the other countries represented in Table 1 are Western countries. MI as an object of scientific study, therefore, has aroused less interest in the East, despite Japan's contribution.

Between 1991 and 2001, no more than 25 papers on MI were retrieved from *IEEE Xplore* database. During this period, it is possible to observe two periods in which no study was published by the proceedings and journals indexed in the *IEEE Xplore*. The first period lasts from 1992 to 1994, and the second from 1998 to 1999. The peak of publications occurred in 2006, when 15 papers were published. The vast majority (10 papers) were presented at international conferences and workshops and the others (5 papers) were published in journals of Natural Language Processing.

The number of annual publications on MI is shown in Figure 1. MI tends to experience periods of advances, stagnations and setbacks that are interspersed with periods that last an average of two to four years. The first of these period lasted for three years, with only one study published in 2000 and seven papers published in 2002. The period of most obvious decline lasted four years, with 12 papers published in 2014 and only one in 2017.

Figure 1. Papers on MI published per year.



Although less frequent, two short periods of stagnation can be seen, one from 2012 to 2013, and the other from 2018 to 2019. It is worth noting that when the two periods of stagnation are contrasted, the latter points to a decline in the number of publications compared to the first. At the time we carried out this scientometric study, *i.e.*, the end of October 2019, analyzing the dynamics of advances and setbacks and considering the period of 28 years, it is difficult to assume the next movements of the scientific community on the field. Based on the fact that before and after the first period of stagnation (from 2012 to 2013) the field experienced small advances, we can conjecture the possibility of advances, even if modest, for the coming years. Nonetheless, the history of advances and setbacks in short periods of time, for no apparent reason, leads us to consider that only the database can provide us with reliable longitudinal images of developments in studies on MI.

The 137 papers were published in 25 conference proceedings and nine journals. Table 2 shows the main publishing sources that published more than five papers on MI. The first column contains the title of the event or journal, the second column contains the number of papers published and, in the third column, the percentage of publications in relation to the 137 papers within the *corpus*. Out the eight main publishing sources, only *IEEE Transactions on Audio, Speech and Language Processing* is a journal, which unequivocally illustrates the importance of conference events for scientific communication and diffusion in the field of MI.

Table 2 also shows that the set of the eight main publishing sources includes 44 papers, that is, 32% of all papers, indicating that the majority (68%) of the papers were published in conference proceedings and journals with less impact. The proceedings of the *Fourth International Conference on Spoken Language Processing*, the main publication source shown in Table 2, for example, published seven papers, which represents only 5.10% of the total papers published. This means that, in addition to the eight publication sources listed, a large number of papers on MI have been spread to different journals and conference proceedings. Conclusions of this type show that, in order to carry out more comprehensive future scientometric studies on MI, the researcher will have to include as many publication sources as possible.

Table 2. Main publishing sources on the subject of MI.

Title of the event (conference) or journal	Number of papers	% of 137
Fourth International Conference on Spoken Language Processing (ICSLP '96)	7	5,10
IEEE International Conference on Acoustics, Speech, and Signal Processing 1997	6	4,37
IEEE Transactions on Audio, Speech and Language Processing	6	4,37
IEEE Workshop on Automatic Speech Recognition and Understanding 2003	5	3,64
IEEE International Conference on Acoustics, Speech, and Signal Processing 1997	5	3,64
IEEE International Conference on Acoustics, Speech, and Signal Processing 1997	5	3,64
IEEE Workshop on Automatic Speech Recognition and Understanding 2003	5	3,64
Fourth IEEE International Conference on Multimodal Interfaces	5	3,64

After the publication of a paper, it is possible to follow, through statistical data provided by the databases, and even by *Google Scholar*, the number of new papers in which it was cited. The more a study is cited, the greater its impact. Hirsch (2005) proposed a calculation to quantify the productivity and impact of researchers based on their most cited papers. Called the h-index, this calculation indicates the number of papers with citations higher than or equal to that number. A researcher with h20, for example, has 20 published papers that received 20 or more citations (Thomaz, Assad, & Moreira, 2011).

Table 3 shows the authors with more than 10 published papers followed by their respective h-indexes. From 433 authors, only three have at least 10 published papers. The number of papers published by these authors within the *corpus*, however, cannot be related to their respective h-indexes, since the calculation of this index takes into account a much wider universe of publications and citations. Alex Waibel, for example, published 03 papers less than Satoshi Nakamura, even though he has a h-index of 85. This indicates that the *corpus* retrieved from the *IEEE Xplore* database cannot be taken as a basis for assessing the scientific impact and productivity of the authors. In addition, Yuqing Gao, who had the same number of publications as Alex Waibel, has not yet had her h-index calculated by the databases or by *Google Scholar*.

Table 3. Authors with the highest number of publications.

Author	Number of papers	H-index
Satoshi Nakamura	16	47
Yuqing Gao	13	-
Alex Waibel	13	85

The degree of impact of the 137 papers can be analyzed, otherwise, by comparing the papers most cited in later papers. Table 4 shows papers cited by more than 100 other papers. The paper "Verbmobil: The use of Prosody in the Linguistic Components of a Speech Understanding System" (Noth *et al*., 2000) is cited by 214 papers and none of its authors is among the three most productive authors shown in Table 3. This fact makes even clearer that the data obtained from *corpus* cannot be used to understand the degree of impact and productivity of the 433 authors.

The most cited papers deals with the Verbmobil MI system, funded by the German government. The second most cited paper was written by a Spanish researcher, affiliated to a Spanish institution. The third most cited study is authored by Japanese researchers, affiliated to Japanese institutions. Only after the fifth most cited study USA appears with other countries. This means that although USA is present in the vast majority of the 137 papers, Germany and other countries have managed to create a greater impact in the field of MI studies.

Table 4. Most cited papers in the *corpus*.

Paper Title	Country	Citations
• Verbmobil: The use of prosody in the linguistic components of a speech understanding system	Germany	214
• Finite-state speech-to-speech translation	Spain	162
• Speech-to-text and speech-to-speech summarization of spontaneous speech	Japan	156
• Text-independent voice conversion based on unit selection	Germany / Spain	130
• JANUS: a speech-to-speech translation system using connectionist and symbolic processing strategies	Germany / USA	118
• Dictionary learning for spontaneous speech recognition	Germany / USA	117
• JANUS-III: Speech-to-speech translation in multiple languages	USA	117
• Verbmobil: The evolution of a complex large speech-to-speech translation system	Germany	110
• The ATR multilingual speech-to-speech translation system	Japan	104

Table 5 shows the number of authors in contrast to the number of papers. About 60% of the papers have between one and four authors, with an average of 3.16 authors per paper. The tendency is three authors per paper and only five papers have one author. This dataset indicates that MI has been carried out by a large number of collaborative studies.

Table 5. Number of authors per paper.

Number of authors	Number of papers	% of 137
1	5	3,64
2	17	12,40
3	36	26,27
4	24	17,51
5	26	18,97
6	11	8,02
7	2	1,45
8	6	4,37
9	1	0,72
10	1	0,72
11	3	2,18
13	1	0,72
14	1	0,72
15	2	0,72
16	2	0,72
18	1	0,72

3.2 Network scientometric analyses

The network scientometric analyses were made both by using the COCI[2] scientometric dataset, which uses the numbers of the *Digital Object Identifiers* (DOI) of each paper; and by the elaboration of data networks through the file extension .ris (Research Information Systems). COCI was chosen after several tests with the other dataset available by VOSviewer showed that this was the only one capable of retrieving the information from the 137 papers within the *corpus*.

The first category referring to network scientometric analyses is the co-authorship. According to Glänzel and Schubert (2004, p. 257), this type of analysis is one of the most tangible and well-documented forms of scientific collaboration, making it possible to safely track all aspects of scientific collaboration networks. One can, for example, track the projects that have received the most funding, because the two major factors that characterize the 'huge science' are large-scale funding and team work: team work requires large personnel, which, in turn, is strongly dependent on the financial support available for the research (Glänzel & Schubert, 2004). Thus, the more researchers study together, the larger the project tends to be and the greater financial resources it tends to receive.

Table 6 shows the ten authors who have the most co-authorship connections amongst the 137 papers on MI. The number of co-authorship connections is shown in the third column of the table in descending order. The numbers in the third column of the table indicate the strength of the co-authorship links. A co-authorship link is the relationship between two authors within the co-authorship network. The greater the strength of the co-authorship link, the greater the number of publications that a researcher has with other authors (Eck & Waltman, 2018, p. 4).

The German researcher Alex Waibel, for example, has published 11 papers in co-authorship, and he has co-authorship links with 64 other authors. The Japanese researcher Satoshi Nakamura, in his turn, is co-author of 12 papers, but he has a connection with only 52 other authors. The German researcher, therefore, stands out in relation to the Japanese researcher much more for the team work rather than for productivity. The same is true in relation to the Spanish researcher Alon Lavie in comparison to Satoshi Nakamura.

Table 6. Co-authorship network.

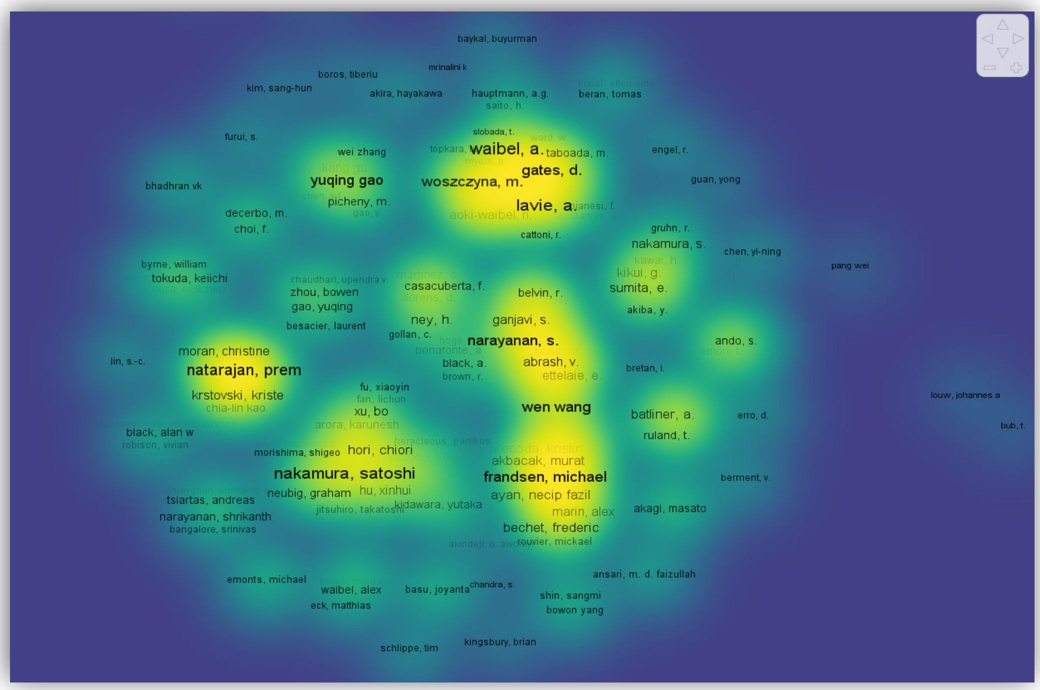
Authors	Number of papers	Co-authorship links
Alex Waibel	11	64
Alon Lavie	8	54
Satoshi Nakamura	12	52
Prem Natarajan	7	41
Rohit Prasad	7	41
Michael Frandsen	3	37
Arindam Mandal	3	37
Shrikanth S. Narayanan	4	37
Jing Zheng	3	37
Shirin Saleem	5	35

[2] http://opencitations.net/index/coci

The co-authorship density map in Figure 2 shows how the co-authors are clustered according to the relationship they establish with each other within the *corpus*. Authors who appear in central areas with 'vibrant' colors on the map have greater co-authorship connections and authors who appear in peripheral areas with 'less vibrant' colors have less co-authorship connections.

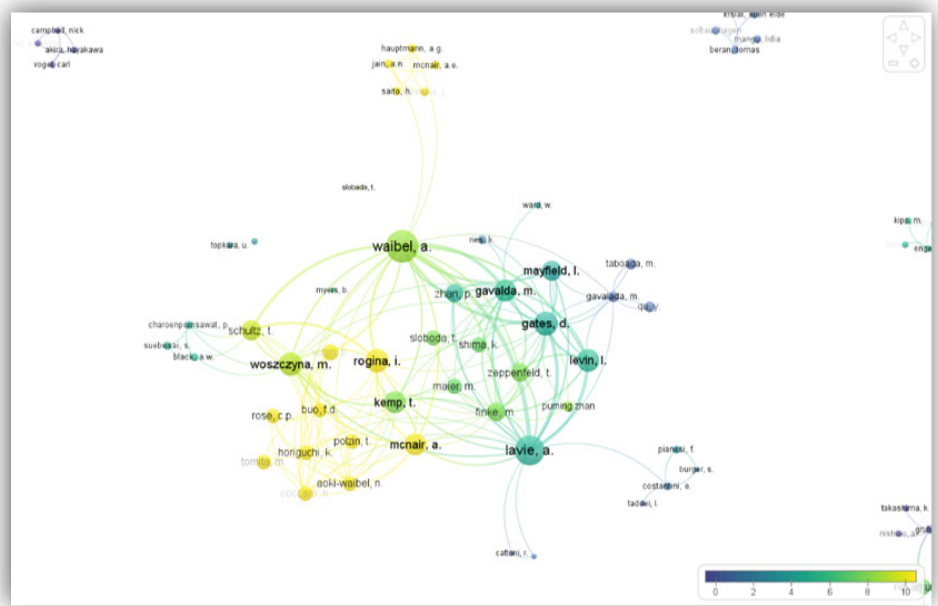
Although the map in Figure 2 shows many author clusters, in Figure 3 the VOSviewer zoom tool was applied to the cluster of authors around the researcher Alex Waibel, the author with the largest number of co-authorship connections. Based on this zoom view, it is possible to observe other authors and their respective levels of influence through the map.

Figure 2. Visualization of the co-authorship density map.



The color nuances in Figure 3 follow the 'average citations' scale for each author. Thus, although the researcher Alon Lavie has more co-authorship connections than researcher Monika Woszczyna, he has a lower average of citations. In addition, the zoom visualization makes it possible to verify that even in central clusters such as Alex Waibel, there are several authors with less impact orbiting the periphery of the cluster, as is the case of the researchers Maite Taboada and Roldana Cattoni.

Figure 3. Network view of the map of authors.



The next category of the network scientometric analysis is the co-occurrence of keywords. Keywords are considered the most basic elements for the representation of concepts (Chen & Xiao, 2016), and have been widely used in the mapping of knowledge areas. Studies such as those by Chen (2006), and Xie, Zhang and Ho (2008), for example, start from the analysis of keyword co-occurrence for the detection of study objects with high potential for future studies and trends within certain areas of knowledge. According to Chen and Xiao (2016), most studies that take into account the co-occurrence of keywords focus more on identifying research topics rather than on the appropriate keyword selection process for future analysis.

We chose to map the main keywords that are used in the 137 scientific papers. Therefore, no filter was applied for the selection of specific keywords, nor for their hierarchical order.

VOSviewer has detected 231 keywords in the 137 papers, which means that each study has, on average, 1.68 keywords. Table 7 shows the 10 keywords that most co-occur. *Machine translation* is the most frequent keyword and it is also the one that establishes the highest number of connections with other keywords, as shown in Figure 4.

MI, as previously mentioned, is composed of three technologies: ASR, MT and TTS (Waibel & Fügen, 2008). The keywords corresponding to each of these technologies can be seen in Table 7: *automatic speech recognition/asr*; *machine translation*; and *speech synthesis,* respectively. The fact that *machine translation* is the most frequent keyword indicates that MT is the most prominent and discussed technological component within the *corpus*.

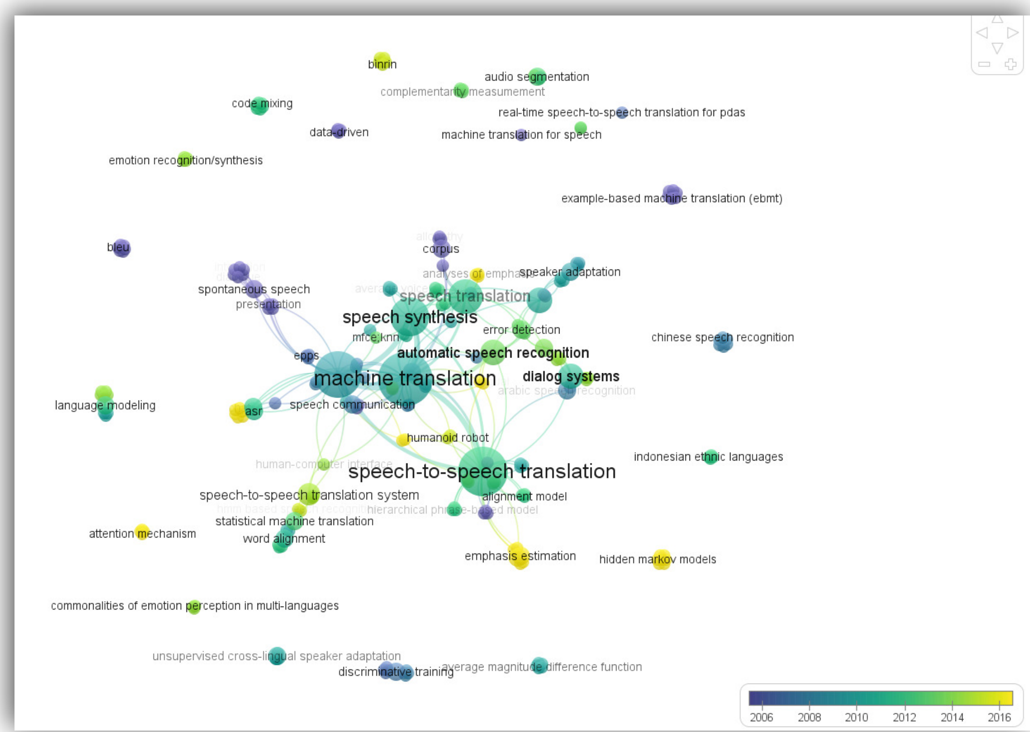
Table 7. Keyword co-occurrence network.

Keywords	Number of occurrences	Co-occurrence link
machine translation	17	49
speech-to-speech translation	14	41
speech recognition	13	39
speech synthesis	9	28
speech translation	7	19
automatic speech recognition	4	12
speech-to-speech translation	4	12
spontaneous speech	2	12
semiannual risk assessment	2	11
dialog systems	4	11

As for frequency, it is noteworthy that the keywords *speech synthesis* and *automatic speech recognition* occur only nine and four times, respectively. In a universe composed of 137 papers, that is, 137 opportunities for these keywords to occur, there seems to be little interest from the researchers to select these two technological components as keywords (with core importance) for their studies.

In this paper, we have decided not to submit any terms normalization file, so VOSviewer considers *speech-to-speech translation* and *speech to speech translation* two different keywords. The same occurs with *automatic speech recognition* and *asr*, its abbreviated form. The absence of normalization does not affect our data analysis, as in a previous study Freitas and Esqueda (2017) had already found the terminological variability in studies on MI.

Figure 4. Network view of the keyword map.



The next category to be addressed is the bibliographic coupling. According to Grácio (2016, p. 84), bibliographic coupling shows the relationship between two papers based on the number of common references cited by both of them. Proposed by Kessler in 1963, bibliographic coupling method group papers based on bibliographic coupling units. The coupling unit is a reference item used by two papers, according to Kessler (1963 *apud* Grácio, 2016). Two papers are bibliographically coupled if they have at least one reference item in common.

Table 8 shows the ten papers with the highest bibliographic coupling, and Figure 5 shows the network view of all bibliographically coupled papers. The titles of the papers shown in the table and on the map are automatically created by VOSviewer and do not necessarily correspond to correct citation standards. To know the title of the study one can just move the cursor of the *mouse* over the title that appears in VOSviewer.

Table 8. Bibliographic coupling network.

Papers	Coupling link
Do *et al*. (2017)	33
Liang *et al*. (2010)	31
Ayan *et al*. (2013)	30
Nakamura *et al*. (2006)	29
Fu-Hua *et al*. (2004)	26
Matsuda *et al*. (2013)	25
Noth *et al*. (2000)	24
Gu *et al*. (2006)	22
Besacier *et al*. (2006)	22
Akagi *et al*. (2014)	20

VOSviewer bibliographic coupling network shows only the bibliographically coupled papers and not the papers responsible for the coupling. In Table 8, for example, we see that Do *et al*.'s paper (2017) has a link value of 33, which means that 33 papers cause Do *et al*. (2017) to be bibliographically coupled. This does not mean, however, that the paper in question is bibliographically coupled to 33 other papers.

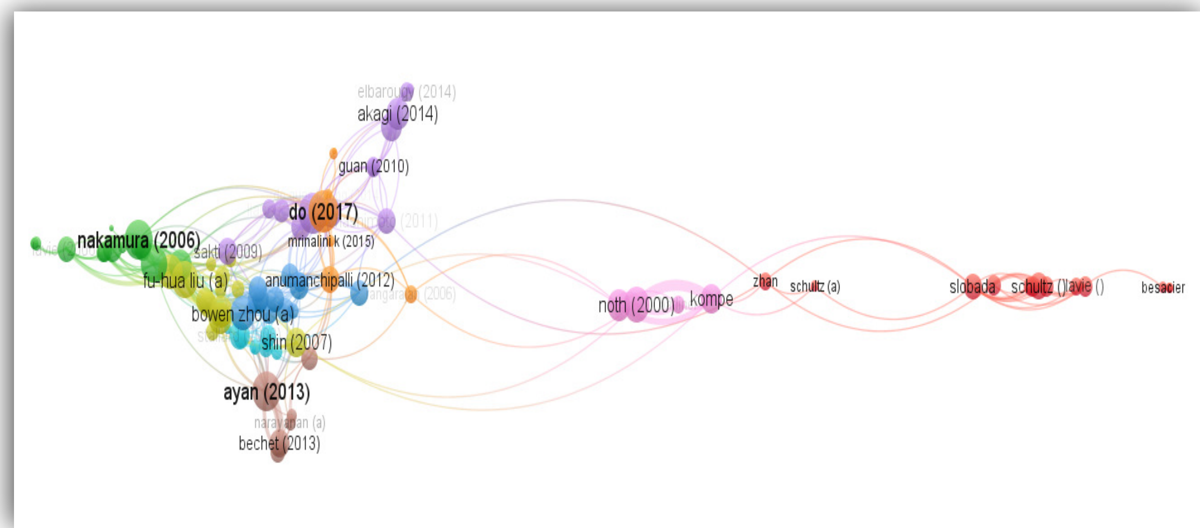
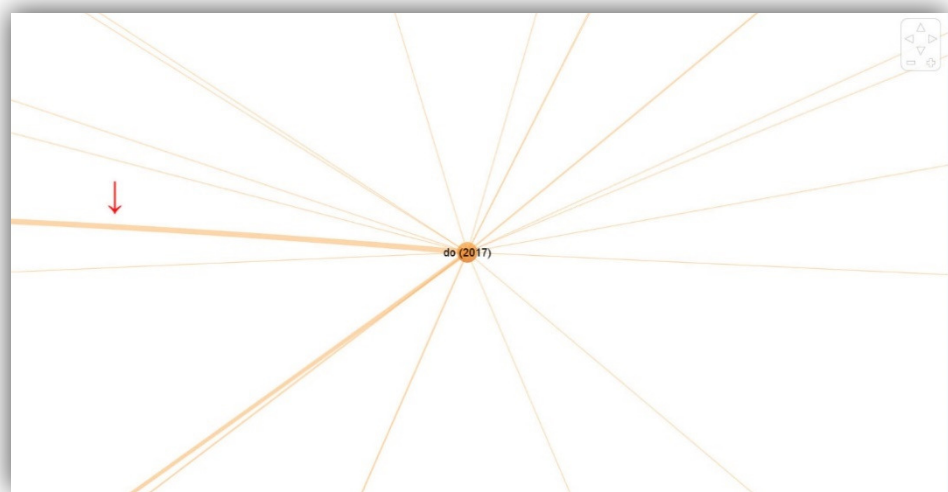


Figure 5. ***Network view of the bibliographic coupling map.***

To see how many papers Do *et al.*'s paper (2017) is bibliographically coupled to, it is necessary to zoom in to the network view of the map. Figure 5, for example, shows that Do *et al.* (2017) is coupled with 19 papers within the *corpus*.

In addition, the thickness of the lines in Figure 6 indicates the number of papers responsible for the bibliographic coupling of two papers. The thicker line, for example, pointed by a red arrow, indicates that Do *et al.*'s papers (2017) share seven reference items, that is, both are bibliographically linked by seven papers.

Figure* 6. *Network view of the bibliographic coupling map.



The last category to be addressed is the co-occurrence of terms in the titles and abstracts of the 137 papers in the *corpus*. This type of analysis is used to identify the main areas of research within a given topic (Dong & Chen, 2015). VOSviewer has detected 2,576 terms in the 137 papers. As the number of detected terms is very high and this would make it difficult to visualize them through the map, we have decided to select only those terms that occur at least ten times. Thus, we obtained a total of 49 terms.

Table 9 shows the ten most relevant terms in the titles and abstracts of the 137 papers. As with co-authorship, the relevance[3] of terms does not depend on the number of occurrences. The term *speech*, for example, occurs 305 times, but it is less relevant than the term *emphasis*.

The table of the most relevant terms, however, contains the terms separated from their respective contexts, which can difficult the analysis. The term *emphasis*, for example, refers to "prosodic emphasis" (Tsiartas *et al.*, 2013), information that is only possible to be retrieved if we apply a direct search on the papers. The term *speech*, even when contextualized, seems to be too generic and may appear as *speech features*; *part of speech*; *speech acts*; *speech understanding systems* etc.

[3] The method for calculating the relevance of terms is explained in *Text mining and visualization using VOSviewer* (Eck & Waltman, 2018).

The term *bleu* refers to the algorithm BLEU (*Bilingual Evaluation Understudy*), used to assess the quality of texts translated by machine translation systems (Papineni *et al.*, 2002). This indicates that this evaluation method is extensively explored by MI and that, since BLEU is based on human translation of texts, human translation methods also influence MI.

The presence of the term *Japanese* indicates that most of the MI systems study Japanese. The term *task* may indicate that papers on MI are more interested in the translation task than in the product itself. And although it appears sparsely in keywords, at least in titles and abstracts, the term *speech synthesis* is more relevant than ASR and MT.

Table 9. Most relevant terms.

Terms	N. occurrences	Relevance
emphasis	17	2.99
speech	305	2.26
bleu	11	1.71
japanese	13	1.38
task	32	1.30
speech synthesis	23	1.30
term	14	1.21
user	32	1.13
system	166	1.08
state	23	1.06

Figure 7. Visualization of map overlay of more relevant terms.

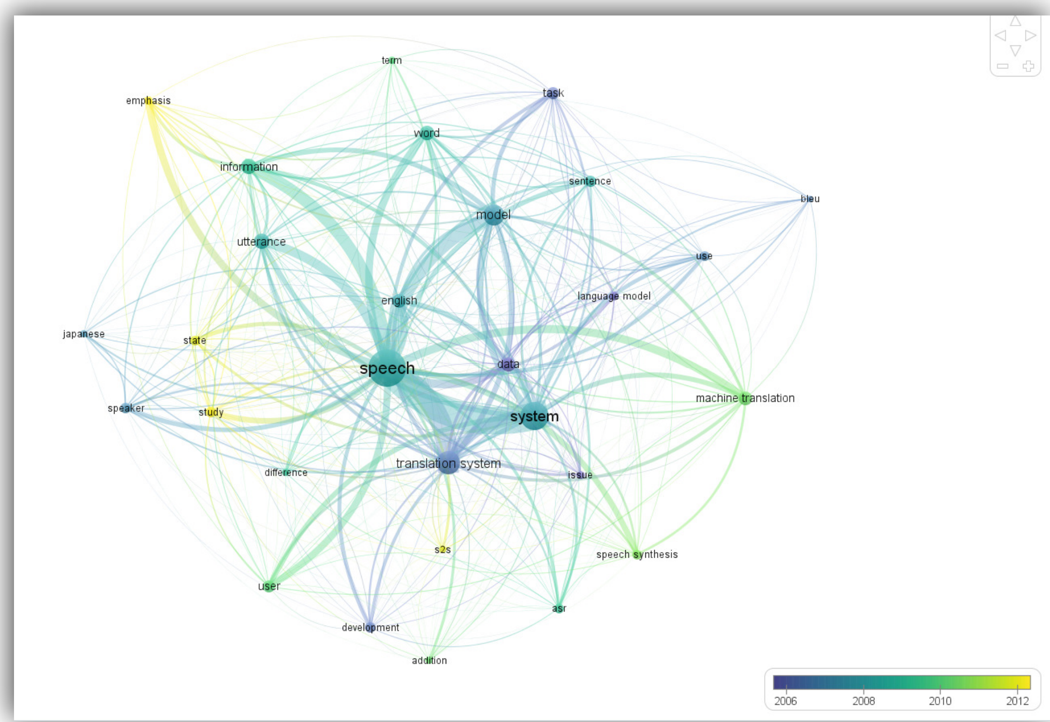


Figure 7 shows the network formed by the 49 most relevant terms within the *corpus* according to the average number of publications per year in which they are cited. Differently from the other elements analyzed in this paper, the map of the most relevant terms does not present disconnected terms in the perimeter of the map. This is due to the fact that we have chosen to show only those terms that have at least 10 occurrences.

The map with the most relevant terms shows that the term *speech* is related to most of the other relevant terms and its ramifications extend directly and indirectly to terms such as *machine translation*, which is found on the periphery of the map and which refers to a technology that besides composing MI systems, it is also a totally independent technology and prior to MI (Pöchhacker, 2004).

4. Summary and future research directions

The scientometric maps and the general bibliographic information presented in this paper offer an overview of MI research. It corroborates the fact that MI has been gaining ground in the context of interpreting technologies (Braun, 2006).

As previously mentioned, this study is limited to analyzing only the publications available in the IEEE Xplore database circumscribed in the period from 1991 to 2019, contributing to our previous findings (Freitas, 2016; Freitas & Esqueda, 2017; Esqueda & Freitas, 2019). Future studies, for example, may extend data recovery to new databases and a greater number of papers over a more comprehensive period.

In addition, it is worth noting that VOSviewer is a complex tool that works with a large number of variables, so that the maps produced through it can offer quite different aspects depending on the choices the researcher takes along the process of data analysis and network construction. We recognized, therefore, the impossibility of exhausting the topic and, like any technology, MI is subject to advances and setbacks of various kinds that can be constantly measured.

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