Review of AI-based methods for chatter detection in machining based on bibliometric analysis

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Abstract

To improve the finish and efficiency of machining processes, researchers set out to develop techniques to detect, suppress, or avoid vibration chatter. This work involves tracing chatter detection techniques, from time–frequency signal processing methods (FFT, HHT, STFT, etc.), decomposition (WPD, EMD, VMD, etc.) to the combination with machine learning or deep learning models. A cartographic analysis was carried out to discover the limits of these different techniques and to propose possible solutions in perspective to detect chattering in the machining processes. The fact that human expert detects chatter using simple spectrograms is confronted with the variety of signal processing methods used in the literature and lead to possible optimal detecting techniques. For this purpose, the bibliometric tool R-Tool was used to facilitate a bibliometric analysis using specific means for quantitative bibliometric research and visualization. Data were collected from the Web of Science (WoS 2022) using particular queries on chatter detection. Most documents collected detect chatter with either transformation or decomposition techniques.

Keywords Bibliometrics · Chatter detection · Time–frequency analysis · Signal processing · Machine learning · Deep learning

1 Introduction

Historically, chatter is described by the father of machining [1] as the most obscure and delicate problem of all that confronts the machinist. In the case of castings and forgings of various shapes, there is probably no rule or formula that can accurately guide the machinist in making the cuts and maximum speeds possible without producing chatter. A few decades later, firstly in a Slovak book [2] and then in international publications by the documents [3–5], the stability lobes theory showed that it was possible to solve the chatter problem. Self-excited vibration frequency called chatter is still the most famous vibration phenomena in machining and is detrimental to surface finish quality and tool life [6]. Chatter is primarily manifested by the regeneration of waviness caused by the interaction between the material surface and the tool at given rotational frequencies of the spindle and by the interaction of one mode or several modes. Several researchers have studied the technique of detecting chatter in vibration signals, for example, the authors [7] and [8]. These are the cutting force, acceleration, sound, and electric current signals, fluently used to monitor the state of the systems [9].

Several signal processing algorithms have been successfully applied to chatter detection, such as Short-Term Fourier Transform (STFT) [10, 11], Wavelet Transform (WT) [12, 13], Wavelet Packet Decomposition (WPD) [14], Hilbert–Huang Transform (HHT) [15–17], empirical mode

Highlights

- Bibliometric analysis on chatter detection techniques in machining processes.
- Effectiveness of AI methods combined with transformation and decomposition techniques.
- Research areas mainly cover manufacturing, mechanics, and automation control systems.
- Application of signal processing techniques in chatter detection with their advantages.
- Challenges of deep learning models to solve problems of performance and explainability.

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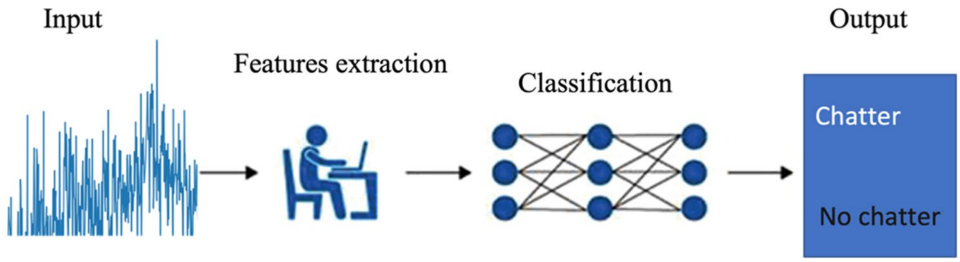


Fig. 1 The deep learning model for binary classification [29]

decomposition (EMD) [18, 19], Variational Mode Decomposition (VMD) [20, 21], and Local Mean Decomposition (LMD) [22].

Generally, this signal processing-based detection is performed in three progressive steps: signal collection, feature extraction, and defect detection or identification [23]. Previously, chatter detection was established based on the engineers' abundant experience and mainly based on acoustic human analysis of the process. It is equally essential to monitor the condition of the tool and detect any anomalies that may occur during machining to prevent any dangerous situations [24]. In any machining operation, the cutting tool's life directly affects the process's quality and cost. By monitoring the condition of tools, it is possible to eliminate problems such as accelerated wear and breakage of tools and chatter during machining. This paper reviews the literature on techniques for detecting or identifying vibration-induced chatter in this paper. Several vibration mitigation techniques, including stiffening in machine tools or part-holder, and active or passive damping techniques, also exist [25, 26]. By monitoring and analyzing the vibration signals near the tool and the workpiece, not only the chatter but also the state of the machine tool can be detected effectively, and even allow us to develop a digital twin of the machine [27]. The predominant analytical methods use so-called stability lobe diagrams to predict the stability of machining processes. Time–frequency processing models, using a wide range of mathematical transforms and decomposition, have been used in chatter detection, whether in milling, turning, drilling, or grinding. All these sophisticated methods have some difficulties in detecting unobvious chatter (i.e., when there is not a substantial increase in root mean square (RMS) vibration level or even sound noise) and accurate industrial noisy vibration signals (rarely considered). These difficulties must be confronted by the fact that on-field human chatter experts use only spectrum and spectrogram representations to detect chatter, and thus probably, research should investigate more what information can be extracted directly from spectrums and spectrograms.

Quite recently, deep learning (Fig. 1) has appeared as a general concept that refers to the newest and most successful group of methods based on neural networks and has proven to be very effective in many fields.

To reduce the human contribution to the diagnosis and detection of faults, integrating machine learning theories (Fig. 2) with vibration analysis is a promising way to automate the procedures currently used by the document [28].

This article aims to provide a comprehensive review of chattering detection techniques, from time–frequency processing techniques to Artificial Intelligence (AI) techniques, and identify the already most promising and emergent ones.

To perform this extensive analysis, the bibliometric tool R-Tool was used by the document [30], an R package intended to facilitate bibliometric analysis, based on the open source software R, one of the most influential and flexible software environments for statistics and data science. This analysis provides a new perspective on the evolution of techniques for detecting, identifying, or suppressing chatter in machining by developing a taxonomy of knowledge for research topics in the field.

An in-depth analysis of past and current studies on the evolution of chatter detection techniques is performed on 655 research publications between 1985 and 2022. This study provides insights into the application of AI in chatter detection in machining and particular industrial needs

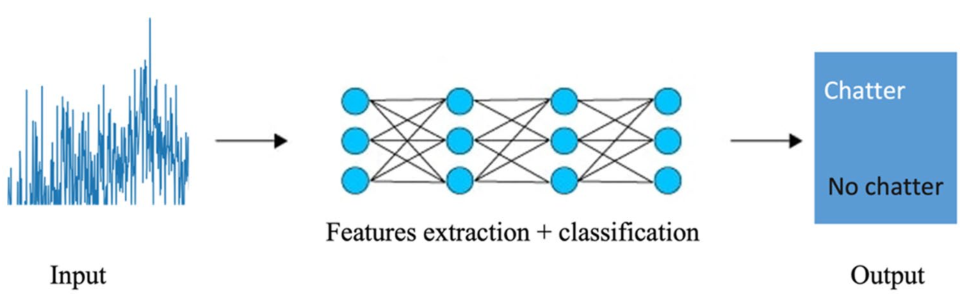


Fig. 2 The machine learning model for binary classification [29]

regarding the detection of chatter without having to provide information on the amplitude of the vibration signal because the signal may be more or less intense depending on the type of sensors and their positions, or the operating frequencies of the machine, which can be difficult to collect or erroneous due to the presence of reducers or gearboxes, for example. Another perspective is the opportunity to use unsupervised learning to detect phenomena not identified a priori by the human expert. Finally, the explainability of the AI technique would facilitate the use and exploitation of AI results.

The rest of the article is organized as follows: Sect. 2 describes the bibliometric analysis, Sect. 3 presents previous work on time–frequency and AI processing techniques for detecting chatter in machining, and Sect. 4 presents challenges with opportunities and solutions in machining. The article concludes with Sect. 5.

2 Bibliometric analysis

2.1 Information about data

The bibliometric analysis will identify key metrics related to this section's sources, documents, authors, keywords, and countries. The bibliometric analysis will identify key metrics related to sources, documents, authors, keywords, and governments. In this section, the analysis will also allow us to classify and visualize the publications according to their impact, interest, frequency of citations, and collaboration in the research field. The appeal of the bibliometric analysis is to acquire new information that will give an overview of the target field and serve as a perspective subject for scientific research.

Data for this search were collected from the Web of Science (WoS) database. All articles and journals included in the analysis were written in English. Since systematic literature reviews rely on careful selection of keywords, it was decided that the keywords (chatter detection, time–frequency processing, machine learning, and deep learning) should appear in the title, the keywords, or the text. For the data search strategy, the following queries were used in the WoS database ("Web of Science April 2022"):

- ("chatter detection" OR "chatter identification" OR "chatter recognition" OR "chatter suppression")
- ("chatter detection" OR "chatter identification" OR "chatter recognition" OR "chatter suppression") AND ("Machine learning" OR "Deep learning" OR "Artificial Intelligence")

The first query was run to retrieve 679 research publications, including 350 publications in engineering manufacturing, 290 publications in engineering mechanical, and 173 publications in automation control systems (Fig. 3).

Table 1 presents the preliminary information about the data collected on WoS between 1985 and 2022. This table reports information such as the number of documents obtained, the search period, author keywords, and keywords. The authors provide the author keywords in this case (1546) words. The keywords plus (652) are generated from an algorithm to extract the words frequently appearing in the title references, not only the document titles or author keywords. The bibliometric tool allowed us to know the appearance of the author (1425), authors of single-author documents (11), authors of multi-author documents (1414), the average number of authors per document (2.25), and the collaboration index (2.27). Figure 4 shows the classification of publications by type of document, with 482 articles, 155 proceedings papers, and 14 reviews.

Figure 5 shows the publication frequency during the period 1985–April 2022. The scientific publications on chatter detection techniques started to reach 40 publications per year in 2017, and the evolution peaked in 2019 with 83 publications. Between January and April 2022, there were 26 articles on chat detection.

The growth of the annual scientific production is due to the enlargement of the observation base with the addition of new publication media (journals, conference proceedings, chapters of collective works, etc.) in the database as (WoS and Scopus). This addition occurs in two ways, and first, the observation bases integrate the existing journals after a selection process to better cover the world's scientific production. The journals are also created by developing new scientific themes [31]. Figure 6 illustrates this growth using the more generic term "machining" as a query.

In the present study, it is noted that chatter detection is seen almost as much from the manufacturing side as from the mechanical side. In contrast, a priori, it would only be seen from the manufacturing side and possibly as an automatic system. Most of the publications are less than 6 years old, and many studies have focused on the development of analytical and numerical algorithms for chatter prediction [32–34].

Integrating concepts like the Internet of Things (IoT) has significantly shaped the manufacturing industry. The development of science and technology has enabled the integration of concepts such as IoT because volumetric and reliable multi-sensor technologies are integrated to collect data. The growth in the size of data in the industry and the storage and processing of big data highlights the need for data-driven manufacturing as a critical component of intelligent manufacturing. To this end, research has focused on combining physics-based models (FFT, WT, etc.) with data-driven computational models (machine learning and deep learning) [35, 36].

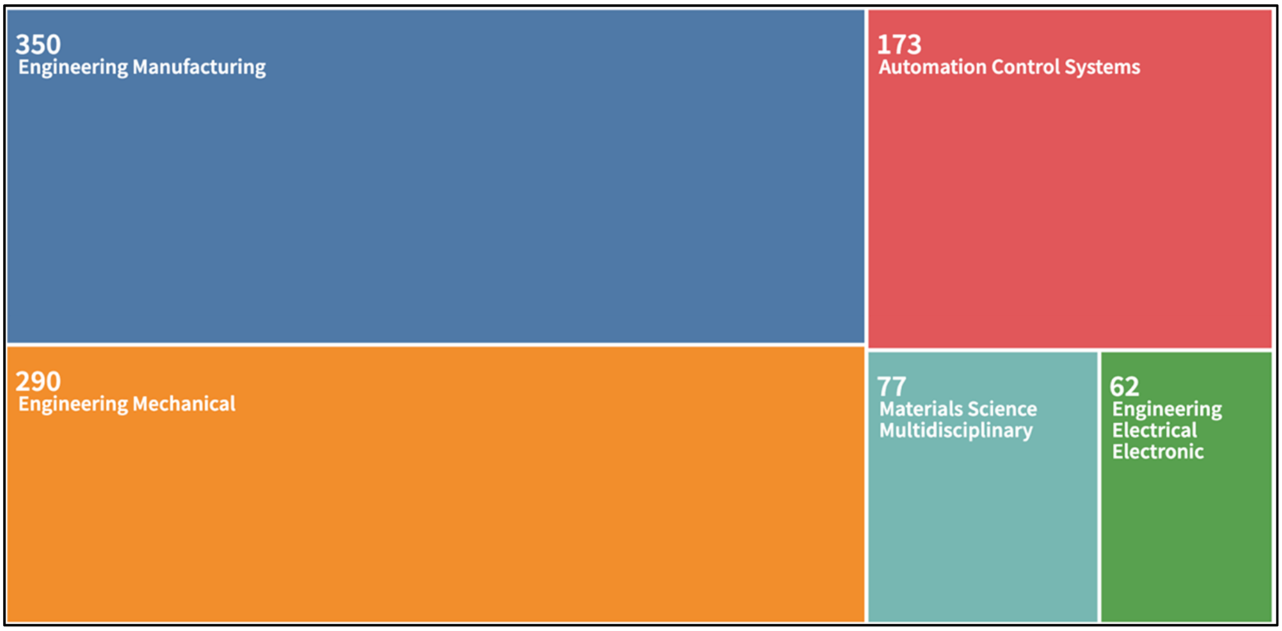


Fig. 3 Ranking of publications in different research areas

2.2 Sources

To show the dynamics of the growth of the productivity of the journals, their impacts and number of citations, and their network collaborations, Table 2 presents the most productive journals according to the number of publications (NP), the number of citations (TC), and the impacts (h-index, g-index, m-index). H-index [37] is defined as the number of publications for which the author has received at least h-citations. G-index is an author-level measure proposed by Egghe [38], which is calculated based on the distribution of citations received by publications of a given author, given a set of articles ranked in descending order of the number of citations they received. M-index [39] is the number of publications for which the author received at least h-citations.

"International Journal of Advanced Manufacturing Technology" is the most productive journal (94) as the number of publications or more than 25% of the articles. "International Journal of Machine Tools & Manufacture" comes in second position (44) and "Mechanical Systems and Signal Processing" with 31 publications in the third position. However, it should be noted that the most productive journal is not necessarily the most cited. For example, "CIRP Annals-Manufacturing Technology" is more mentioned than "Mechanical Systems and Signal Processing" since it is less productive than "International Journal of Advanced Manufacturing Technology" (Fig. 7).

In Fig. 7, the vertical axis shows the names of the scientific publication journals, and the horizontal axis indicates the number of journal citations in the research on chatter detection techniques. The journals are listed in descending order. The International Journal of Machine Tools & Manufacture is on top with 2661 (TC), followed by CIRP Anales-Manufacturing Technology 2146 (TC) and International Journal of Manufacturing Technology, etc.

2.3 Authors

The bibliometric tool counts the local citations of an article and an author in the most cited references. The number of local citations presents the number of appearances of an author in the documents collected for this study. According to Fig. 8, Y. Altintas is the most cited author (1585 citations in total), the number in the circle is the number of local citations, and the width of the line depends on this number.

Y. Altintas is probably the most famous researcher on machining vibrations (Table 3). He explained most of the chatter process by making the equation and enriching the AI models with the mechanical ones. He demonstrates with a numerical simulation model on dynamic milling that the use of continuously variable spindle speed can be a way to suppress chatter [40]. He was followed by D. Dornfeld (731 total citations), who does not specialize in machining vibration, talk, or AI but has been prolific in precision machining and using sensors. K. Jemielniak shares the same score with G. O'Donnell and R. Teti (726 citations in total), who are classical researchers working for decades on machining. These authors have an excellent knowledge of the field and propose new techniques to detect, identify, or locate chatter for machining stability over time. They are working with D.

Table 1 Primary information about data

Description	Results
Timespan	1985–2022
Sources (journals, books, etc.)	250
Documents	679
Average years from publication	7.13
Average citations per document	18
Average citations per year per document	2179
References	10,565
DOCUMENT TYPES	
Article	482
Article; book chapter	5
Article; early access	6
Article; proceedings paper	14
Correction	1
Letter	2
Proceedings paper	155
Review	14
DOCUMENT CONTENTS	
Keywords Plus (ID)	652
Author's Keywords (DE)	1546
AUTHORS	
Authors	1425
Author appearances	2484
Authors of single-authored documents	11
Authors of multi-authored documents	1414
AUTHOR'S COLLABORATION	
Single-authored documents	12
Documents per author	0.476
Authors per document	2.1
Co-authors per document	3.66
Collaboration Index	2.12

Dornfeld on a paper in Advanced Monitoring of Machining Operations reviewing past contributions and proposing a comprehensive update on sensor technologies, signal processing, and, most importantly, decision-making strategies for process monitoring [41].

The TC index indicates that the authors are not necessarily the most productive. For more details, Fig. 9 presents a network showing the collaboration links between the authors. Their distance in the co-citation links indicates the relationship between the authors. The relationships are strong when the collaboration connection is shorter. In this case, there are ten collaboration groups (X. Liu and Y. Li) are the first group, followed by (H. Gao, M. Wang, and Y. Zhang) and (H. Liu and Y. Wang).

Figure 10 is proposed according to Lotka's law, defining the abscissa axis as the number of papers and the ordinate axis as the number of authors from different fields. The authors can be cited in the documents as the primary author. It can be seen from the figure that more than 1000 authors representing 71% of the authors have written at least one article on the phenomena of chatter.

Figure 11 presents a tree structure that traces the hierarchical composition of signal analysis and chatter detection techniques used in the past. This figure shows the combination of frequency of keywords used in the field of chatter detection, such as "chatter detection," which appeared as a keyword near the following keywords: "wavelet, chatter suppression, stability, model and dynamics," and the keyword "vibration" also appeared with "identification, suppression, regenerative chatter, chatter stability, classification, recognition, etc." in most publications. This representation shows that only the terms "wavelet" and "frequency" have been used for chatter detection. However, several variants of Fourier Transform and other decomposition techniques, like the EEMD decomposition method, have also been widely applied to vibration signals to chatter detection, even if not visible on these global bibliometric indicators.

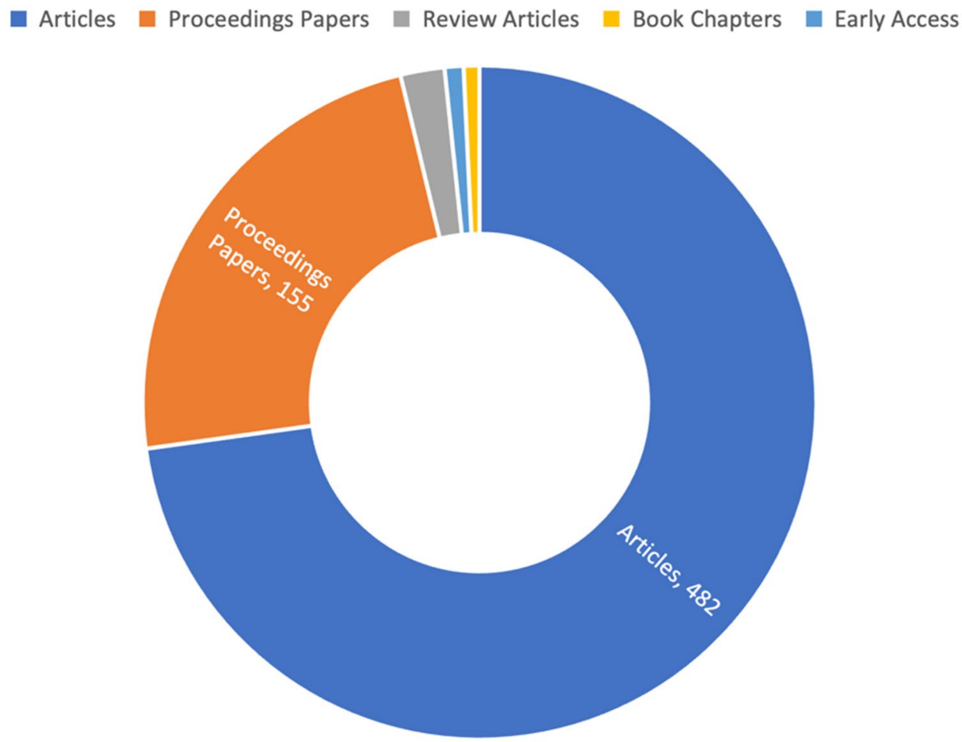
Table 4 presents the most cited papers shared in WoS between 1985 and April 2022. Notably, the article [41] was published in CIRP Annals-Manufacturing Technology with (726 citations). In this article, the authors provide a survey of the development and implementation of sensor monitoring of machining operations. In particular, the paper reviews the past contributions of CIRP in these areas and provides a survey of sensor technologies, signal processing, and decision-making strategies for monitoring machining processes. The scientific paper [42], also published in CIRP Annals-Manufacturing Technology, is in second place with 502 citations. The authors discuss the fundamentals of the chatter stabilization law in machining by addressing non-linear processes.

Moreover, Fig. 12 gives an overview of the top 10 most cited papers in our network of 679 documents (local citations) for intelligent chatter detection. This is to be distinguished from the most mentioned documents globally (global citations), which refer to the total number of citations worldwide. It has been found that chatter detection has attracted the attention of researchers in many other fields.

2.4 Scientific production on the chatter phenomena by country and continent

Table 5 shows that China, Canada (mainly because of the author Y. Altintas), and the USA occupy the first places based on the number of total citations, the frequency of publication, and the average number of citations per article. China is in first place with 3707 total citations on 781 publications, followed by Canada with 1560 total citations

Fig. 4 Ranking of publications by type of documents

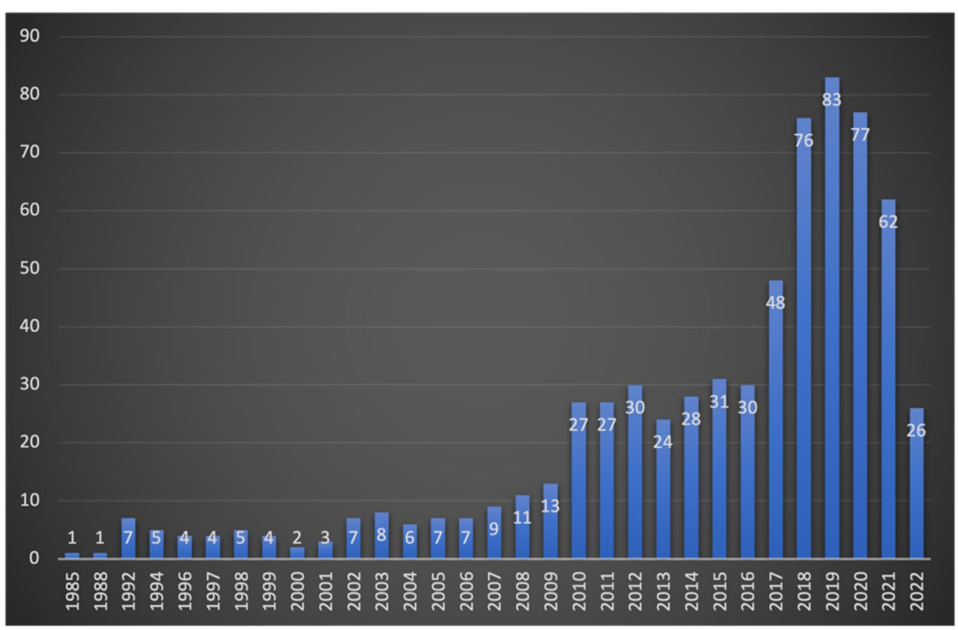


on 75 publications, and the USA, which appears 1256 times in total on 140 publications. It is noted that no African country seems on the table, and only Brazil represents South America, which is generally due to the low development of manufacturing industries and research. Algeria and Egypt are part of this study on the chatter phenomenon, but only with 24 citations on 7 published articles (Fig. 13). In addition, Fig. 14 shows the collaboration network between countries, showing a wide range of interactions.

2.5 Most common technologies or models used for chatter prediction, detection, or stabilization

This section analyzes the most frequent keywords and their co-occurrence levels. These keywords are regarded as the essential elements of the knowledge concept representation that reveal the structure of the research topic. The size of the words in the cloud, Fig. 15, determines the number of occurrences and the density of the words in the publications. It should be

Fig. 5 Annual scientific production



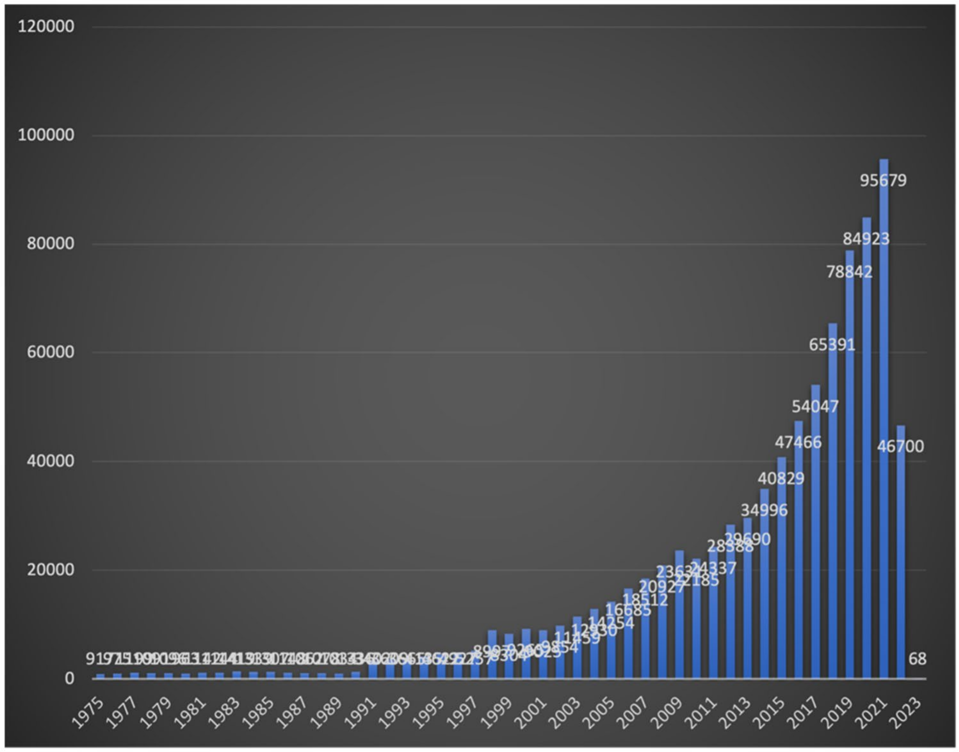


Fig. 6 Annual scientific production using the term "machining" in research

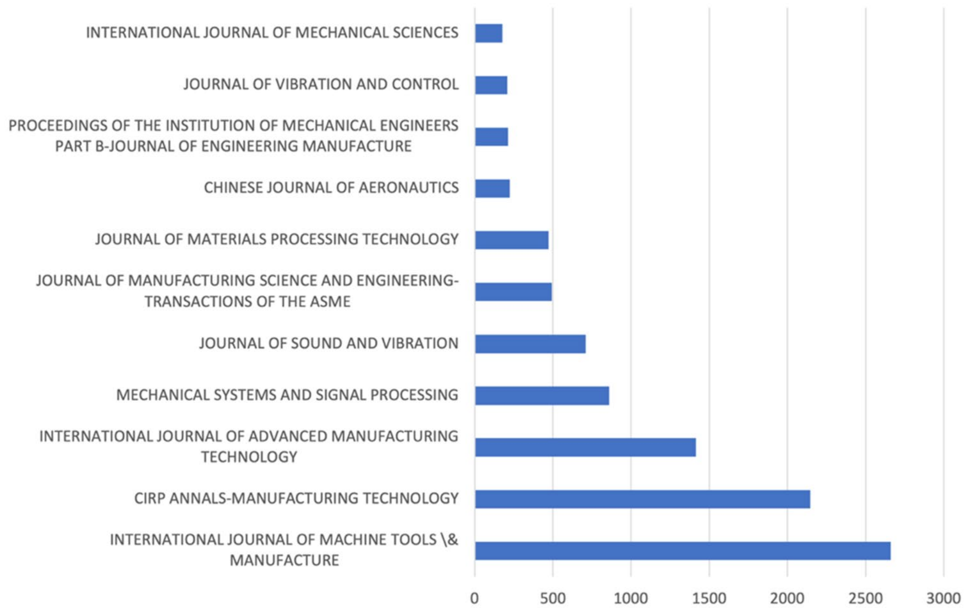
noted that the most frequent word is clearly stability (with 178 occurrences), followed by vibration, prediction, and chatter detection with 122, 115, and 101 occurrences, respectively.

This shows that the physical model ("surface," "tool," "cutting force," "regenerative," etc.) is considered secondary compared to the supposed properties of the signal

Table 2 Sources impact

Sources	h_index	g_index	m_index	TC	NP	PY_start
International Journal of Advanced Manufacturing Technology	21	30	0.78	1414	94	1996
International Journal of Machine Tools & Manufacture	30	44	0.97	2661	44	1992
Mechanical Systems and Signal Processing	17	29	0.49	860	31	1988
Journal of Manufacturing Science and Engineering-Transactions of the ASME	12	22	0.44	493	26	1996
CIRP Annals-Manufacturing Technology	13	18	0.62	2146	18	2002
Proceedings of the Institution of Mechanical Engineers Part B-Journal of Engineering Manufacture	8	14	0.38	214	16	2002
Journal of Sound and Vibration	12	15	0.48	709	15	1998
Journal of Vibration and Control	8	12	0.62	209	12	2010
Precision Engineering-Journal of the International Societies for Precision Engineering and Nanotechnology	7	10	0.58	117	10	2011
Measurement	6	9	1	122	9	2017
Journal of Materials Processing Technology	6	8	0.26	473	8	2000
Journal of Intelligent Manufacturing	5	7	0.17	121	7	1994
Materials	4	6	1	59	6	2019
Advances in Manufacturing	3	5	0.5	32	5	2017
Applied Sciences-Basel	4	5	0.67	29	5	2017
Chinese Journal of Aeronautics	5	5	0.33	223	5	2008
International Journal of Mechanical Sciences	5	5	0.38	177	5	2010
Machining Science and Technology	3	5	0.14	70	5	2002
Mechatronics	3	5	0.14	82	5	2001
Chinese Journal of Mechanical Engineering	3	4	0.23	30	4	2010

Fig. 7 Ranking of journals by several citations



("stability," "vibrations," "chatter") and the goals of detection ("identification," "prediction," "suppression"), and depending on the authors the techniques used may vary, like "wavelet," "Hilbert–Huang transform," and "empirical mode decomposition." The "stability" predominance word shows that chatter is strongly related to the mathematical concept of instability and exponential divergence to an infinite, associated with a very simplified model when the machinist knows that there is no such thing, just a change in vibrational amplitude and frequencies. Authors have sought to control the phenomena of vibration chatter by proposing techniques for tool stabilization [48], chatter suppression [49, 50], identification or detection of chatter phases [51–53], or prediction of chatter with artificial intelligence techniques in different machining operations [26, 54, 55].

Figure 16 presents a conceptual structure map of the authors' keywords. This map applies the MCA analysis technique, a multivariate exploratory technique proposed in the biblioshiny tool. Figure 16 shows the co-occurrence network of the authors' keywords divided into three clusters. Fifty words most used by the authors are distributed between the clusters. The red cluster has thirty-three elements, the blue cluster has eleven elements, and the green cluster has six elements. The red cluster predominates with words related to machining processes (milling, end milling, boring, turning,

Fig. 8 Author local impact by TC index

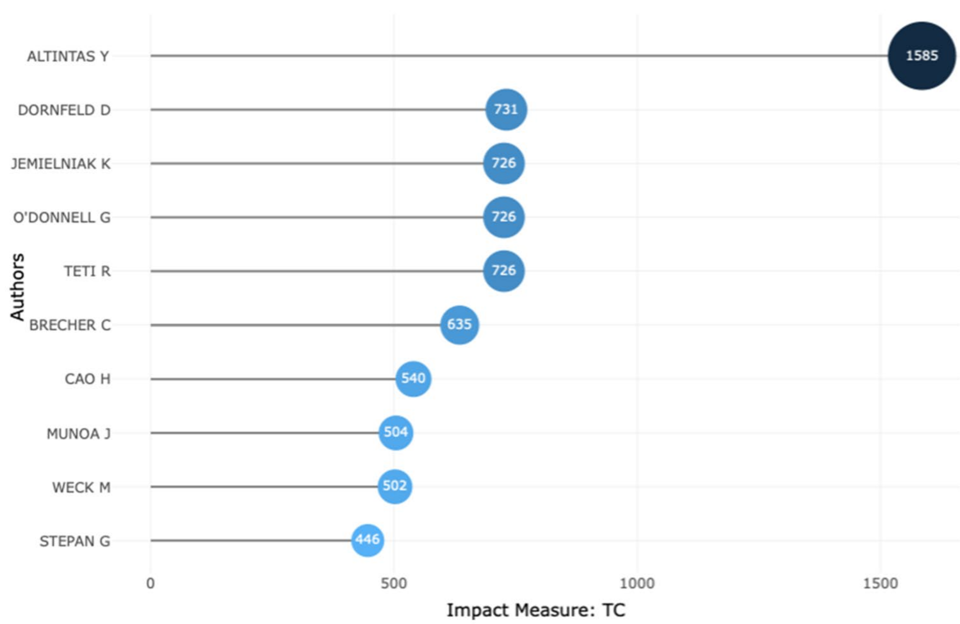


Table 3 Author local impact

Authors	h_index	g_index	m_index	TC	NP	PY_start
Y. Altintas	12	16	0.4	1585	16	1992
D. Dornfeld	2	2	0.2	731	2	2010
K. Jemielniak	1	1	0.1	726	1	2010
G. O'Donnell	1	1	0.1	726	1	2010
R. Teti	1	1	0.1	726	1	2010
C. Brecher	3	5	0.2	635	5	2010
H. Cao	9	15	0.9	540	15	2013
J. Munoa	9	14	0.6	504	14	2009
M. Weck	1	1	0.05	502	1	2004
G. Stepan	6	13	0.4	446	13	2008
X. Zhang	10	19	1.7	427	19	2017
E. Budak	3	4	0.1	399	4	2000
X. Chen	8	12	1	394	12	2015
Z. Chen	7	8	0.4	348	8	2007
Z. Dombovari	4	6	0.6	336	6	2016
X. Beudaert	4	5	0.5	323	5	2015
D. Mei	6	6	0.4	319	6	2007
S. Smith	3	3	0.1	301	3	1992
C. Liu	7	12	1	292	12	2016
M. Sortino	3	4	0.2	292	4	2008

grinding, etc.). The blue cluster represents the words about the methods of transformations and extraction of characteristics of the vibration signal. The green cluster focuses on the machining cutting tool and their damping with words like (machine tool, machining, vibrations, active damping, and machine learning).

This analysis groups extensive data with multiple variables in a low-dimensional space to produce an intuitive cluster graph. It uses the plane distance to illustrate the similarity between the keywords. Keywords close to the center point indicate that they have recently received particular attention. For example, in the red cluster, the keyword "detection" is in the center, surrounded by words like turning, vibration control, and boring.

Several elements are analyzed about the dynamics of the keywords and the trend topics. First is the evolution of the authors' keywords (Fig. 17). After 2016, some keywords significantly increased faster than others: identification techniques (including wavelets) and chatter suppression. Also, it shows the trend of keywords with a minimum frequency of 10 appearances. It appears that between 2019 and 2020, research on chatter identification, monitoring, and, more recently, machine learning has increased. In detail, different techniques such as artificial intelligence (neural network, SVM, CNN, etc.) and signal processing (HHT, EMD, FFT, STFT, etc.) have been involved. These techniques have made it possible to extract the features of the signal to assist the human expert in making decisions and very often serve as a basis for training artificial intelligence methods (Fig. 18).

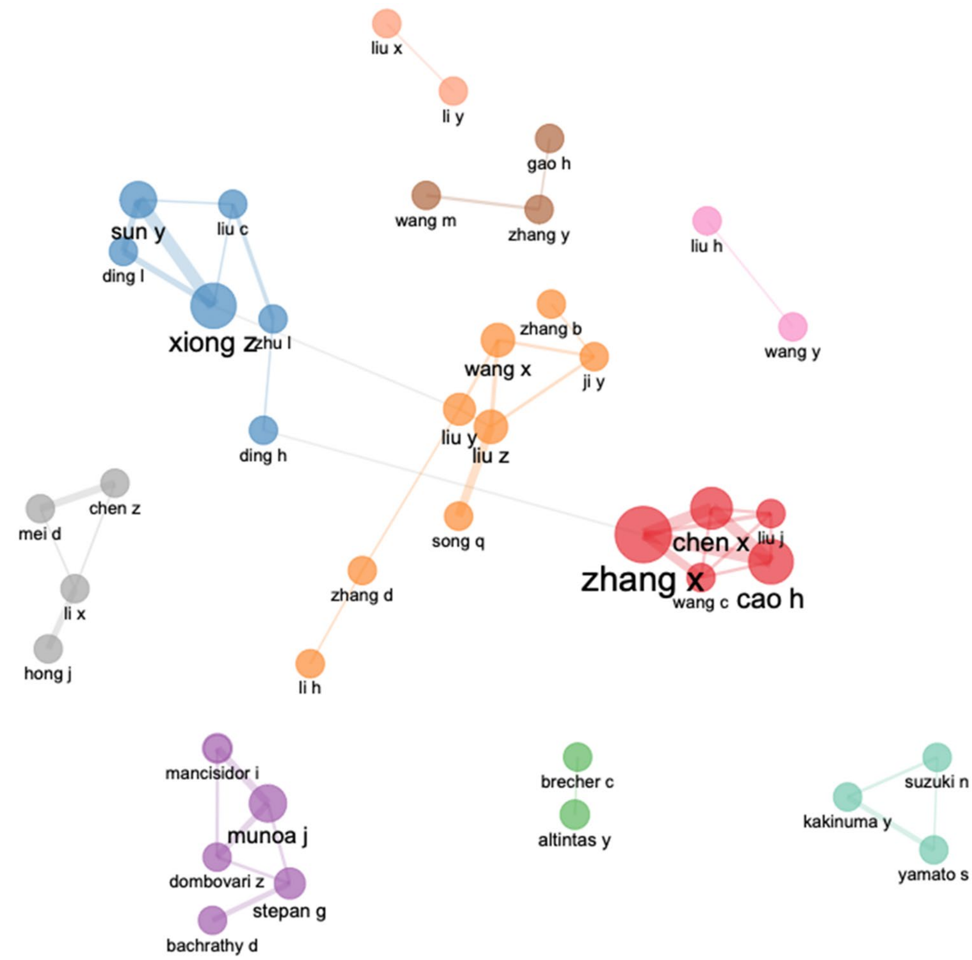
2.6 Artificial intelligence applications

In this part, a second recording was made by adding some keywords ("Machine Learning" OR "Deep Learning" OR " Artificial Intelligence") to see the extent of the application of artificial intelligence techniques for chatter detection in machining.

Most studies on vibration chatter detection have used signal processing techniques or physics-based numerical models exploiting vibration data.

With the emergence of artificial intelligence techniques in various fields, researchers have combined signal processing techniques and AI models (machine learning and deep learning) for feature extraction and decision-making in chatter detection. This particular analysis query was used to filter out articles that use AI to identify or detect chatter. The query result gives 75 out of 679 documents using AI techniques; Fig. 20 shows the trend of AI usage over the years for chatter detection. Most of these documents were published between 2016 and 2021, and machine learning models (SVM and ANN) are the most used. Figure 20 shows that the first published papers on chatter detection using AI techniques date back to 1994. It is in 2020 that more than 19% of these publications have been done, i.e., 15 papers. It can be seen in the list of the most cited documents globally (Table 7) with the document [45], which proposed an approach to detect and identify the vibration chatter using WT to extract the signal features. SVM decision-making (classification) was cited 165 times. In the second position,

Fig. 9 Collaboration network



the document [56] is a review article on the concept of intelligent machining, and this article is mentioned 131 times. The document [57] is in the third position with 67 citations total. These authors also proposed a methodology for intelligent detection of the chatter phenomena in a milling process using an artificial neural network. All this bibliographic information demonstrates that quite apart from the initial groups of authors historically publishing on machining chatter, new authors are developing new techniques for chatter detection (Fig. 19).

Fig. 10 The frequency distribution of scientific productivity

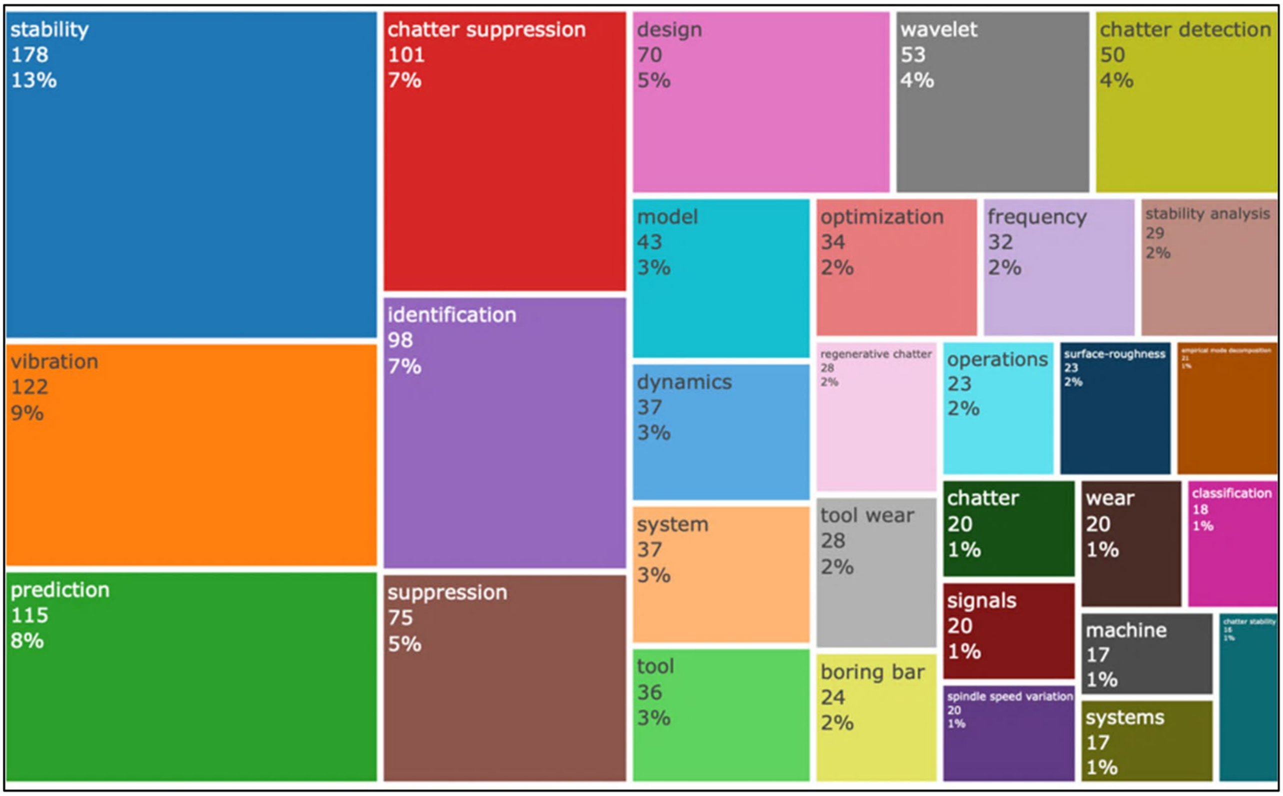


Fig. 11 Treemap for the description of the hierarchical composition

Table 6 shows in detail the list of the ten authors of the two groups in order of the number of documents published.

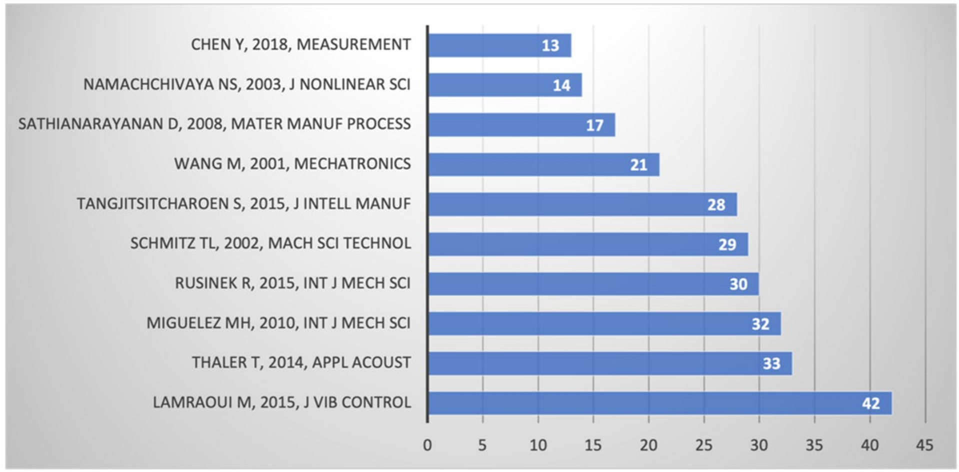
A look at the words of the authors using the new techniques shows a word cloud containing the most used AI (machine learning or deep learning) techniques, the physics-based signal processing models, and the machining operations involved (Fig. 21). Among the machine learning models used by the authors are the SVM classifier, one of the most popular supervised classifiers in the literature, artificial neural networks, and the discrete Markov model. The most interesting is the appearance of the keyword deep learning in detecting chattering by using generally transfer learning in machining processes (milling, turning, drilling, etc.). Transfer learning aims at completing the learning of a machine learning model, previously trained to solve a given task, to enable it to perform a similar task.

Table 7 shows the most cited papers in the automatic chatter detection research community. Most of the documents in Table 8 were published between 2016 and 2022 for automatic chatter detection on machining processes

Table 4 Most global cited documents

Paper	Total citations	TC per year	Normalized TC
Teti et al. [41]	726	55.85	11.44
Altintas and Weck [42]	502	26.42	5.78
Munoa et al. [25]	290	41.43	10.25
Abele et al. [6]	286	22	4.51
Siddhpura and Pautobally [43]	261	23.73	13.19
Delio et al. [44]	173	5.58	3.04
Yao et al. [45]	161	12.38	2.54
Bravo et al. [46]	159	8.83	3
Sims [47]	147	9.19	4.02
Altintas and Chan [40]	138	4.45	2.42

Fig. 12 Most local cited documents



like (milling, drilling, turning, end milling, etc.). The most frequent physics-based models are FFT, STFT, EMD, WT, and HHT. The use of data-based models frequently Support Machine Vector (SVM), Multi-Layer Perceptron (MLP), and Convolutional Neural Networks (CNN). Another Index Based Reasoner (IBR) technique proposed by the document [58] is used to detect chatter and estimate tool life. IBR is reasoning that ranks the incoming signals utilizing a lookup table after the most descriptive features have been identified with preprocessing (human supervision).

Table 5 Country scientific production on the phenomena of chatter by country and continent in WoS

Country	Frequency	Total citations	Average article citations
China	781	3707	13.24
Canada	75	1560	45.88
USA	140	1256	23.26
Italy	47	1180	62.11
Spain	84	823	32.92
Germany	66	460	21.90
UK	66	395	21.94
Australia	25	391	43.44
India	93	364	9.84
Iran	71	307	10.23
Japan	79	298	12.42
Slovenia	24	281	28.10
Poland	54	150	7.50
Hungary	52	142	8.35
Brazil	32	117	9.75
France	30	109	13.62
Turkey	35	102	9.27
Thailand	16	86	14.33
Singapore	7	70	35.00
Sweden	5	70	70.00

3 State-of-the-art

3.1 Application of signal processing techniques in chatter detection

In general, in machining, the sensors detect non-stationary signals and knowing that the FFT requires a defined time window (classically 0.1 to 1 s in machining), this inevitably introduces a detection delay of the order of a period sampling, and anyway, a distortion related to the fact that the FFT is inaccurate enough to represent a signal with time-varying amplitudes and frequencies. The STFT attempts to compensate for this defect by using a sliding window and multiplying the FFTs, making it possible to identify the changes more finely in the signal. The HHT is not constrained by the assumptions of stationarity and linearity required for the FFT and can generate vibration signal information faster than the FFT. On the other hand, the HHT remains a very empirical method and is known to have difficulties distinguishing close frequencies, which requires eliminating the high-frequency part of the signal, which often appears in machining. As for the STFT, despite the windowing technique, it is limited by the width of the window, which displays the time and frequency resolution. Based on the Heisenberg uncertainty principle [73], this resolution cannot be arbitrarily high, and it is always a question of making a compromise between temporal and frequency resolution. The Wavelet Theory (WT) presented in the document [74] reduced the problem related to the windowing posed on the STFT by using several windows of different lengths. In the WT, the analysis of the high frequencies is carried out with narrower windows to obtain a better temporal resolution and expansive windows for the low frequencies to have an optimal frequency resolution (Fig. 22).

Another WT model, the Wavelet Packet Transform (WPT), breaks down the approximations and details to generate more frequency bands and provide more opportunities

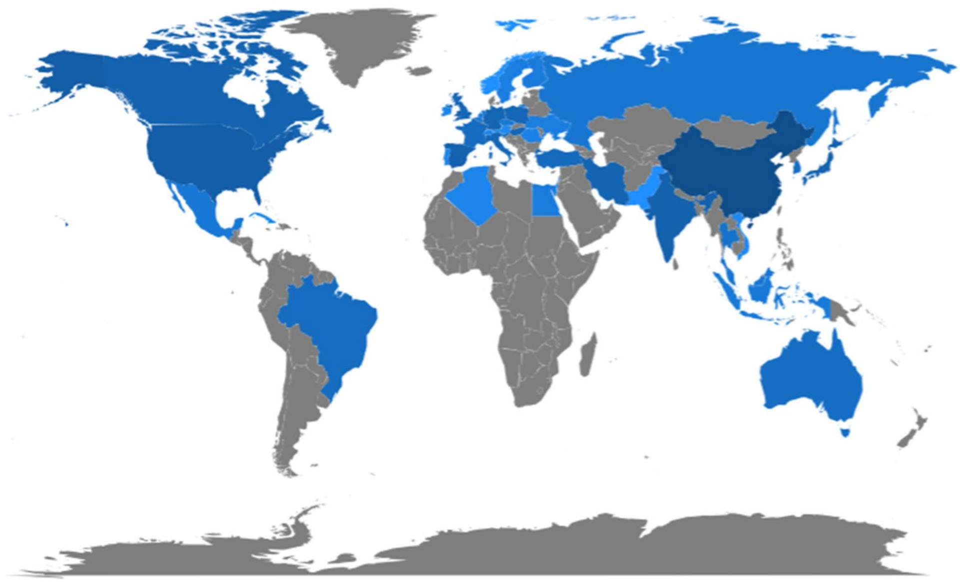


Fig. 13 Map of country scientific production

to get more signal characteristics. Unlike the STFT, the WT, or the WPT, the HHT corresponds more to a process practiced on a data set than a theoretical tool as clearly defined as the previous methods. The HHT is composed of an EMD step to obtain the decomposition of the signal into a quasi-orthogonal basis called Intrinsic-Mode-Functions (IMF). The analysis over time of the frequencies associated with each IMF makes it possible to generate "Hilbert Spectra Analysis" (HSA) to analyze the signal further. The document [75] shows that applying HHT in spectrum analysis provides higher temporal and high-frequency resolution than those offered by STFT.

Table 8 compares the different transformation techniques (Fourier, Wavelet, and Hilbert) based on frequency type, presentation, frequency linearity, stationarity, and feature extraction capability.

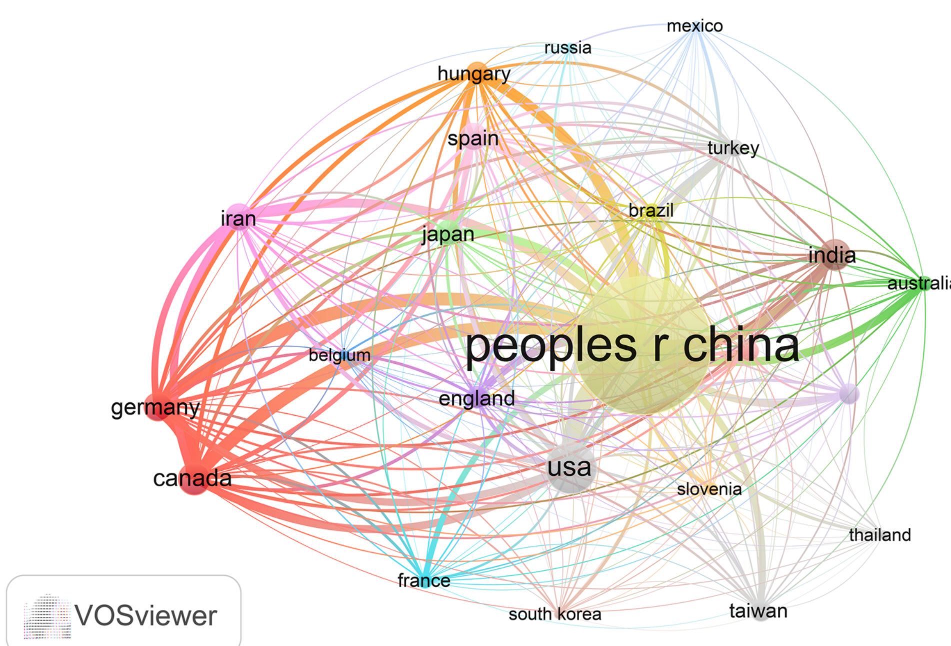


Fig. 14 Network of collaboration between countries at the global level

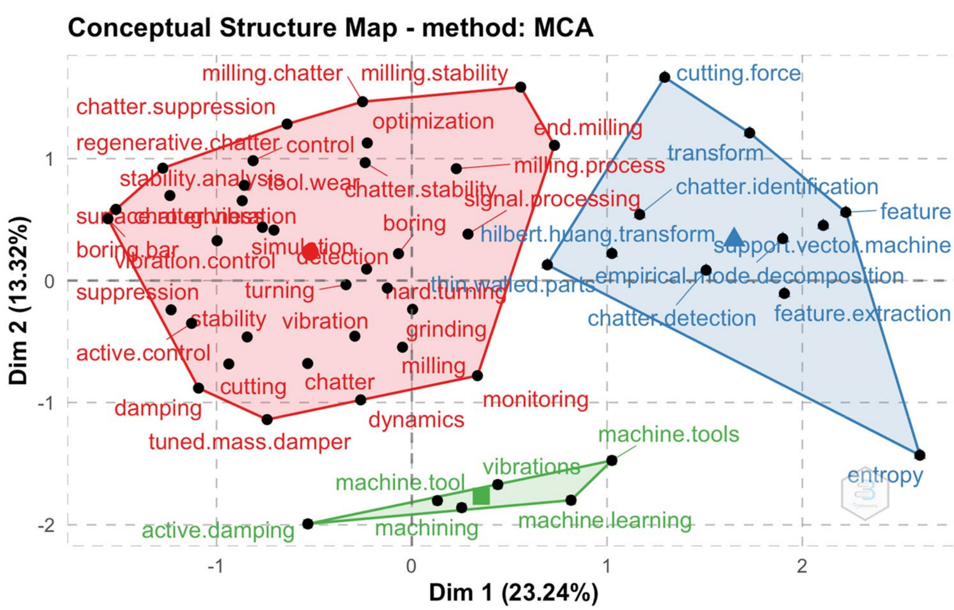
Fig. 15 World cloud

The authors use these techniques to analyze the signal in several areas of machining, such as milling [77–79], turning [75], and rotor system [80].

Reference [43] is a review of research on vibrational chatter in turning operations. They review vibration prediction, detection, and control techniques. They compare different analytical methods for the prediction of chatter stability, such as the Stability Lobe Diagram (SLD), Nyquist diagrams, and the finite-element analysis method. The documents [16, 63] propose a Hilbert–Huang transformation method for early detection of online chatter before part damage. They measure the vibration signal and decompose it into a series of empirical mode functions by applying the ensemble empirical mode decomposition. Hilbert–Huang spectral analysis is then used on the characteristics of the empirical function to calculate the time–frequency spectrum. Because of vibration chatter's nonlinear and nonstationary properties in the milling process, the document [15] proposes a self-adaptive approach: Ensemble Empirical Mode Decomposition (EEMD). They analyze vibration signals with EEMD to extract nonlinear indices as vibration indicators. Then they integrate the sensitive IMF containing the relevant chatter information to obtain a new signal. The two dimensionless nonlinear hands reflected the state of chatter in the time and frequency domain, providing an alternative solution for identifying chatter in the milling process. Since online chatter detection involves signal preprocessing, extracting sensitive features and developing real-time monitoring models are crucial. The document's authors [81] propose a new approach to identify chatter in line milling. This method uses Optimized Variational Mode Decomposition (OVMD) to decompose the cutting force measurements and extract subcomponents containing chatter information using a simulated annealing (SA) algorithm. Approximate and sample entropy detect the onset of chatter, and the results show better performance than the previously mentioned EMD.

The authors [11] experimented with a multisensory configuration composed of sound, acceleration, and cutting force to detect chatter in band sawing. The experimental analysis shows that the sound signal is more appropriate for chatter detection. They adopt a methodology that preprocesses the signal with the STFT to extract features in frequency space, i.e., the height of specific frequency peaks, with an optimal threshold. Quadratic discriminant analysis is applied to the extracted features to detect chatter. The author [78] combines Empirical Mode Decomposition, Wavelet Packet Decomposition (WPD), and Hilbert–Huang Transform (HHT) to identify chatter. Since the IMF change depending on the power spectrum or the frequency amplitude, the empirical mode decomposition is used to select the main features of the signal reconstruction. The WPD

Fig. 16 Conceptual structure map—method: MCA



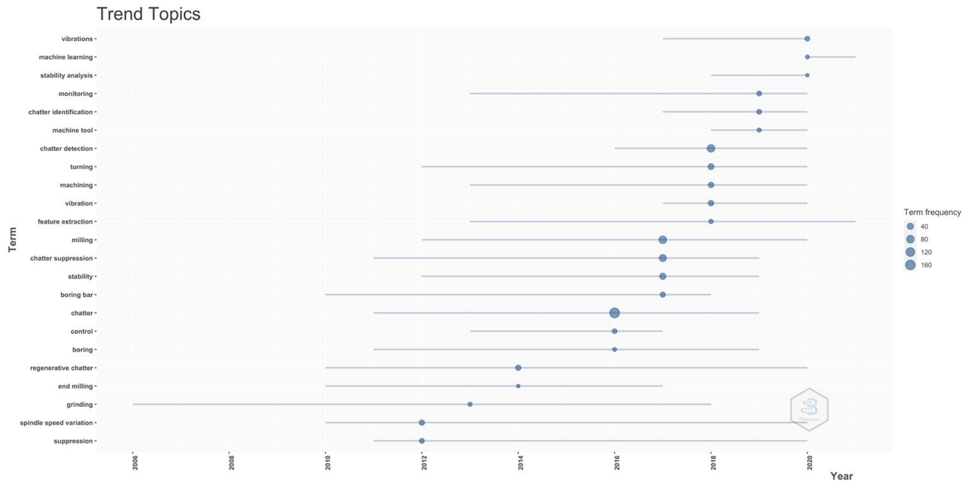


Fig. 17 Keywords plus dynamics

made it possible to reconstruct the signal in two stages using the maximum energy. The HHT model is the distribution of frequency and energy in the time domain. Considering that HHT supports non-stationary and non-linear signals, the document [81] proposes a chatter detection technique for the boring bar by comparing two types of signals from a strain gauge and an FBG sensor by HHT. These signals are then decomposed into several IMF using the EMD technique. The transform is applied to each IMF to obtain the instantaneous frequencies with time and amplitudes. These results show that HHT can be considered a simple and reliable technique to detect chatter vibration. However, like most studies, very far from realistic industrial conditions and chatter is associated with increased vibrational amplitude.

The document [82] presents a chatter detection method based on image analysis of dominant frequency bands from STFT spectrograms. Environmental noise related to chatter and high-energy frequency bands are localized by a squared energy operator of the synthesized FFT spectrum. The proposed feature extraction method is verified under various milling cutting parameters in three classes (stable cutting, slight chatter, and significant chatter). The results show the effectiveness of time–frequency image features of dominant frequency bands for chatter detection, and its performance is better than time-domain feature extraction and wavelet-based methods in terms of the capabilities of separability. This approach is quite like human expert analysis on STFT. However, it is applied to non-realistic

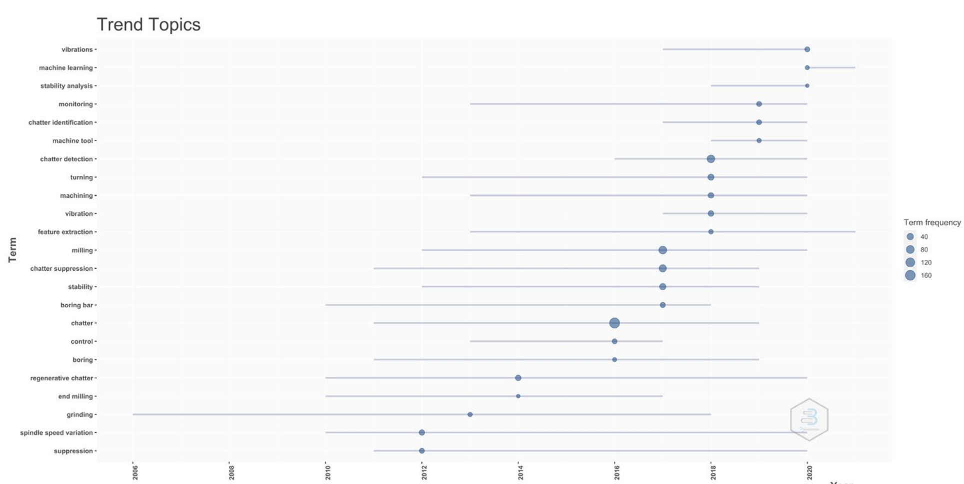
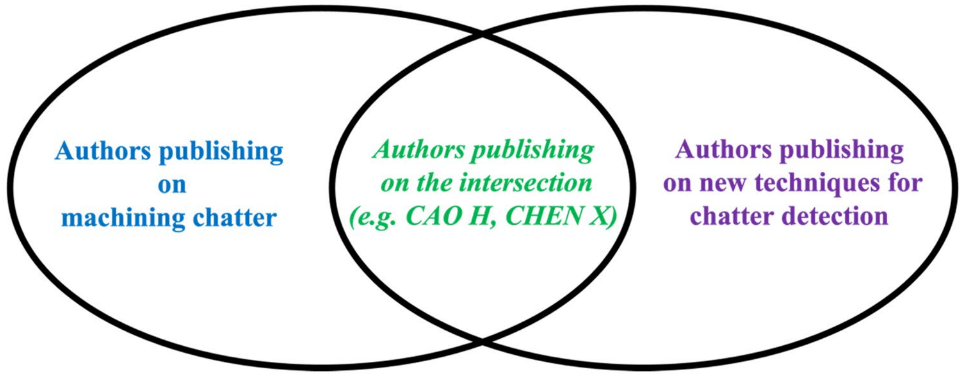


Fig. 18 Keywords trend topics

Fig. 19 Groups of historical authors and authors use new techniques for chatter detection



industrial applications, and chatter is still clearly associated with vibration amplitude, making it difficult to decide the performance of such an elaborate algorithm.

Similarly, the document [83] proposes a system that combines STFT and spectral flattening analysis in the time–frequency domain to identify relevant information on the chatter and transient vibrations from an accelerometer's signal. The proposed system cannot only prevent the tool's failure by detecting the occurrence of chatter but also provides comprehensive information on the condition of the tool. The authors of document [84] detect online chatter by monitoring vibrational energy. Using a Kalman filter, they remove forced vibration forces in the discrete-time domain and all other periodic components. Then, they find the amplitude and the frequency of the chatter between the two passing frequency harmonics of the consecutive teeth using the nonlinear energy operator. The chatter is determined when the energy of the chattering component increases relative to the energy of the forced vibrations. This method detects chatter earlier in discrete time intervals than frequency domain-based methods like FFT.

The wide variety of signal analyses to detect chatter shows that this remains a very delicate task, especially for early detection, i.e., before the amplitude of the vibrations is already significant, and it is too late for the quality of the part. In addition, all these studies are based on laboratory machining tests, therefore without the constraints of noise and the variety of situations to be managed in the industry. Consequently, defining a practical, robust method largely remains, making it possible to quickly identify chatter without needing an expert to fine-tune the detection parameters.

3.2 Application of artificial intelligence techniques in chatter detection

The emergence of Industry 4.0 for increasing productivity and reducing production costs has prompted the use of automatic, unmanned machining centers or intelligent machining systems. In these new systems, the machine tool must be able to automatically perform certain activities such as collision detection and avoidance, tool status monitoring, optimization, or at least adaptation of cutting parameters in a degraded situation, the detection, and, if possible, the

Fig. 20 The evolution of AI techniques in chatter detection

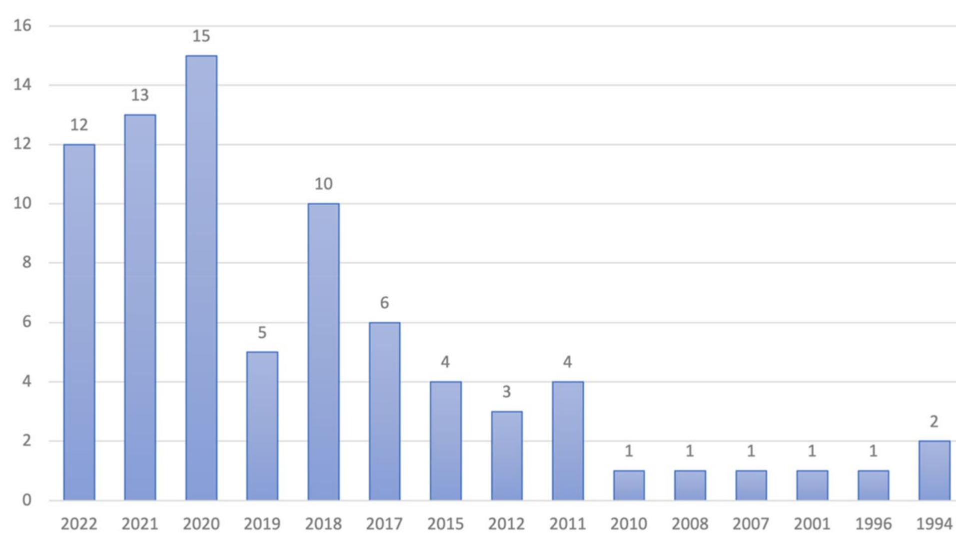


Table 6 The ten most revealing authors for both groups

Historical authors		Authors using new techniques	
Authors	Articles	Authors	Articles
X. Zhang	21	F.A. Khasawneh	4
Z. Xiong	18	B. Sener	4
Y. Altintas	17	B. Singh	4
J. Munoa	16	H.O. Unver	4
H. Cao	15	H. Cao	3
Z. Liu	14	M.C. Chen	3
G. Stepan	14	X. Chen	3
Y. sun	14	J. Liu	3
X. Wang	14	A. Otto	3
X. Chen	13	Y.S. Tarng	3

suppression of vibrations due to chattering. Specifically, the integration of chatter detection systems into the machine tool control unit would be a significant improvement in machining. Thus, the identification and detection of vibrations in machining processes have been an active area of research over the past two decades.

3.2.1 Machine learning

One of the difficulties in studying chatter is that the machining equations learn chatter because the machining equations describing the scribe's appearance are generally nonlinear delay differential equations. Most of the existing tools for chatter identification rely on defining a metric that captures chatter characteristics and a threshold that signals its occurrence. The difficulty of choosing these metrics, usually entrusted to experts, can be eased using machine learning techniques [85]. Machine learning is now commonly used to relate measured vibration signals to machining. It generally consists of three phases: the collection of signals, the extraction of characteristics, and the learning or training of models, commonly called the "signal-characteristics-model" method (Fig. 2). The signal collection aims to collect as many signal patterns and their corresponding machining states as possible [86]. The wide variety of the dataset is the basis for the model to achieve good generalization performance. Feature extraction aims to identify several key feature parameters from the initially recorded signals to determine the relationship between the signal and the machining states. Characteristics are usually defined manually, which requires a great deal of human expertise. Among the machine learning methods used in automatic chatter, detection is the majority of identification techniques that rely on Support Vector Machines (SVM) [87], Artificial Neural Networks (ANN) [59, 88], unsupervised Learning [89], and models of deep learning like the convolutional neural network.

Further study will show the growth of words over the years. One of the first papers using a machine learning method in the 1990s to detect chatter is [65] which uses the neural network to learn the characteristics of the pushing force spectrum in the process of drilling adaptively. In the document [60], the authors designed an observer for a real-time control system to mitigate chatter in a filming process using artificial neural networks. To improve the surface quality and reduce vibration and wear of the cutting tool, the document [57] proposes an approach based on the multilayer perceptron (MLP) and Radial Basis Function (RBF) to detect the chatter in a milling process. In the document

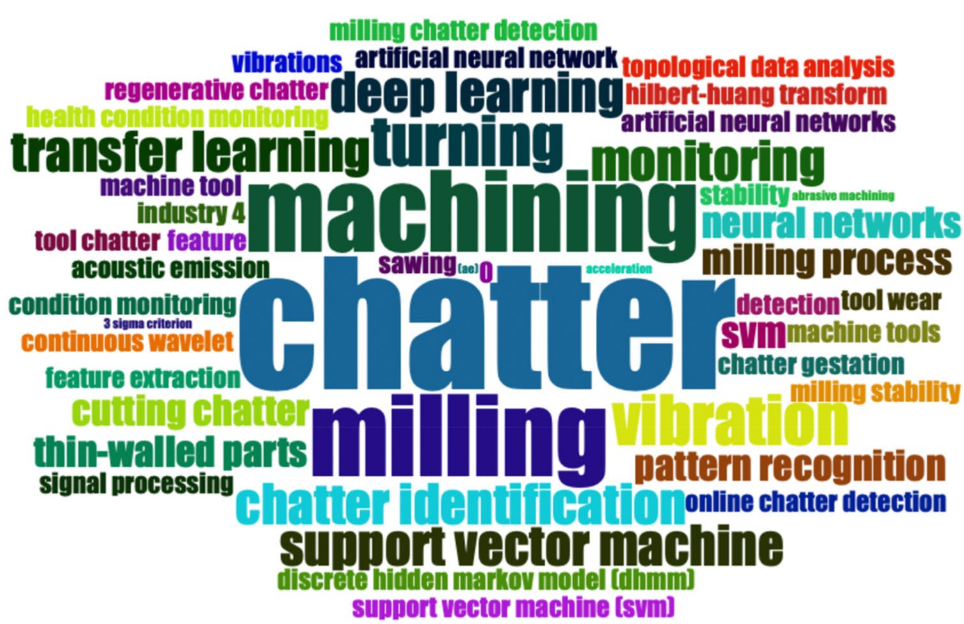


Fig. 21 The word cloud of authors who have published on automatic chatter detection

Table 7 Most global cited documents with their used models

Paper	TC	Data-based models	Physics-based models	Machining process
[45]	165	SVM	WT-WPT	Drilling
[57]	67	MLP	FFT	Milling
[59]	44	MLP	FFT	Drilling
[60]	39	MLP	-	Turning
[61]	33	SVM	EMD	Turning
[58]	32	–	IBR	End milling
[62]	27	SVM	WPT	End milling
[54]	20	CNN	CWT	Milling
[63]	20	–	HHT	Milling
[18]	19	ANN	EEMD	Turning
[26]	18	SVM	WPT-EEMD	Turning
[64]	18	ANN	DWT	Saw milling
[65]	17	ANN	–	Drilling
[66]	17	BPNN	VMD	Milling
[67]	15	SVM	–	Milling
[68]	14	CNN	–	Milling
[69]	12	Hybrid clustering	FFT	Milling
[70]	11	ANN	WPT	Turning
[71]	10	KNN	–	Milling
[72]	10	PNN	WD-HHT	Turning

[72], the authors achieve 100% accuracy for chatter detection by combining WT and HHT for signal feature extraction and a probabilistic neural network for classification, but once again, in a very simplistic machining situation, far from industrial applications, cutting conditions being far outside the tool manufacturer preconization, and with a clear correlation between chatter and vibration amplitude.

To detect chatter, the document [90] used several sensors (sound, spindle vibrations, workpiece vibrations) and created several multilayered neural networks by fitting them to the inputs of different signals and cutting conditions to assess which sensor or combination of sensors could provide a reliable source of information for monitoring the chatter, but without clear answers. In the document [91], the authors used the statistical parameters from the WT as input of a neural network to develop an intelligent chatter detection system. Still, surprisingly the best chatter indicator was correlated with the axial force sensor. This direction is not supposed to vibrate in such a situation strongly. They combined Topological Data Analysis (TDA) and Logistic Regression Classifier (LRC) to have an excellent performance for chatter detection in turning, but this was made only on simulated data. To verify chatter stability, the authors of the document [92] use an artificial neural network model based on a back-propagation network to predict stable cut areas and metal removal rate (but using sensor direction perpendicular to the main chatter vibration direction).

In 2010, the authors of the document [45] combined wavelet transform and SVM for early chatter detection. The SVM classifier was designed for recognition based on the feature vector derived from the standard deviation of the wavelet transform and the wavelet packet energy ratio of the signal frequency band. In the document [61], the authors propose a cutting state monitoring system based on the feed motor current signal. They apply an SVM classifier to the features extracted by the EMD model to develop an intelligent chatter detection system with 95% accuracy. An innovative cutting chatter detection method based on WT and multiclass SVM is proposed by the document [93]. To simplify the computational complexity when binary SVM classification transforms to multi-class classification, the algorithm makes each sample type have a spherical SVM. A combination of Principal Component Analysis (PCA) and SVM is proposed by the document [94] to recognize chatter generation. They extract the characteristics of the vibrational signal with the FFT and label the FFT vectors to serve as input data to the learning model. To increase the accuracy of chatter detection, [95] combines an Adaptive Boosting algorithm (Adaboost) and SVM with training a robust classifier for chatter detection. In addition to the Adaboost–SVM combination, they extract features with a stacked denoising autoencoder considering mislabeled samples. SVM shows its identification capabilities in mirror milling, which is an effective technique for improving the quality of monolithic machined parts. It ensures the mirror relations of the cutter and the support head. The authors of the document [67] use the Q-factor to construct a feature vector by determining the power spectrum of the frequency band. Then, the

Table 8 Comparison between different signal processing techniques

Transform	FFT	WT	HHT
Basis	a priori	a priori	Adaptive (in frequency)
Frequency	convolution: global scale, uncertainty	convolution: regional scale, uncertainty	differentiation: local scale, certainty
Input	ξ: frequency	a: Scaling; b: time shift factor	t: time; x(t): signal
Presentation	Decomposition: $f(x) = \int_{-\infty}^{+\infty} \widehat{f}(\xi) e^{i2\pi\xi x} d_\xi$ Function basis: harmonic (sin, cos) Coefficients: $f(\xi) = \int_{-\infty}^{+\infty} \widehat{f}(x) e^{i2\pi\xi x} d_x$	Decomposition: $f(x) = \sum_{j,k=-\infty}^{\infty} c_{jk} \Psi_{jk}(x)$ Function basis: orthogonal family $\Psi \in L^2(\mathbb{R})$ $\Psi_{jk}(x) = 2^{\frac{j}{2}} \Psi\left(2^j x - k\right)$ $\langle \Psi_{jk}, \Psi_{lm} \rangle = \int_{-\infty}^{\infty} \Psi_{jk}(x) \overline{\Psi_{lm(x)}} d_x =$ $\delta_{jl}\delta_{km}$ Coefficients: $\mathrm{C_{jk}} = \left[\mathbb{W}_\Psi \mathrm{f}\right]\left(2^{-\mathrm{j}}, \mathrm{k}2^{-\mathrm{j}}\right)$ – $\left[\mathbb{W}_\Psi \mathrm{f}\right](\mathrm{a}, \mathrm{b}) = \frac{1}{\sqrt{\lvert \mathrm{a} \rvert}} \int_{-\infty}^{\infty} \Psi\left(\frac{\mathrm{x}-\mathrm{b}}{\mathrm{a}}\right) \mathrm{f}(\mathrm{x}) d_x$ With $\mathrm{a} = 2^{-j}$ and $\mathrm{b} = k2^{-j}$ dyadic dilatation, and dyadic position)	Decomposition: $X(t) = \sum_{j=1}^{n} c_j + r_n$ c_j: intrinsic mode function (cubic splines) r_n: residue function Function basis: cubic splines Coefficients: Obtained by an iterative process with a stoppage criteria (The instantaneous frequency is computed using the Hilbert Transform)
Non-stationary	No (or using Short Time Fourier Transform, STFT)	Yes	Yes
Feature extraction	No	discrete: no, continuous: yes	Yes
Theoretical base	Complete theory	Complete theory	Empirical
Merits	Gets the information on the frequency	Gives both time and frequency domain information	Provides both high temporal resolution and high-frequency resolution
Limitations	Does not evolve in the time domain (or using STFT)	Selection of the basic function	Near frequency distinction, mixing problem (avoided using EEMD)
Application:			
– Milling	– 25 articles	– 70 articles	– 34 articles
– Turning	– 5 articles	– 30 articles	– 8 articles
– Drilling	– 2 articles	– 19 articles	– 1 article
– Grinding	– 2 articles	– 7 articles	– 5 articles

SVM is then used to diagnose and detect milling status. It proposes a methodology for online chatter detection based on WPT and recursive feature removal by SVM at the end-milling process. In the document [96], the authors construct a VMD-SVM model to identify chatter in the robotic milling process. Other authors in the document [71] use a K-nearest neighbor machine learning classifier to detect chatter in the high-speed milling process. They create a cluster containing two categories of cut conditions (chatter condition and normal condition). To facilitate the feature extraction process, the document [97] presents an approach based on the characterization of the time series of the cutting process using its TDA topological features. They integrate the time series as clusters using Takens' theorem, contact details for Carlsson, etc.

Several classifiers like SVM, Logistic Regression Classifier (LRC), Random Forest, and Gradient Boosting are combined to detect chatter. The document [98] proposes a multi-class SVM model to detect chatter phenomena. For this, they study two indicators, on the one hand, the real-time variance of the milling force signals in the time domain, and on the other hand, the wavelet energy ratio of the acceleration signals based on the WPT. Then chatter detection is performed by a trained multi-class SVM. The authors of the document [36] proposed an approach for identifying chatter in the boring process. It consists of merging the characteristics of

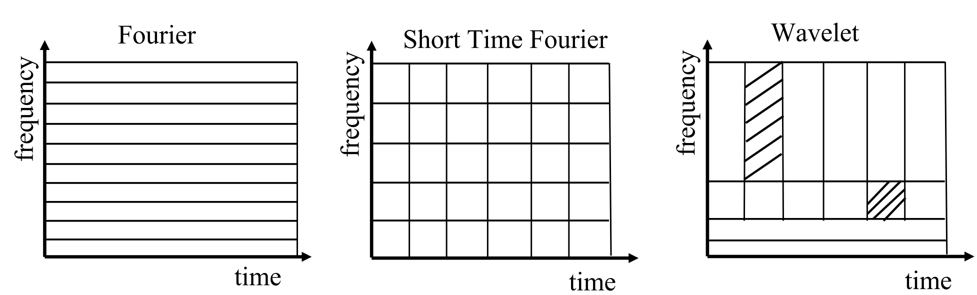


Fig. 22 Signal processing, respectively, with the FFT, STFT, and WT [76]

Table 9 The advantages and disadvantages of machine learning and deep learning methods

Method	Advantages	Disadvantages
SVM	• Good in large spaces • Still efficient in situations where the number of dimensions is higher than the number of samples • Multi-usages	• Difficulty in managing the number of features much higher than the number of samples • The cost of calculating probability estimates is very high • Requires human supervision for the task of identifying features
MLP	• Ability to learn non-linear models • Online learning	• Hidden layer MLPs have a non-convex loss function in which there is more than one local minimum. As a result, different random weight initializations may lead to different validation accuracy • MLP model needs to define a number of hyperparameters such as the number of hidden neurons, layers, and iterations • MLP is sensitive to the scale of the characteristics • Requires human supervision for the feature extraction task
CNN	• Do not require human supervision for the feature extraction task • Precise image recognition and classification • Weight sharing • Minimize the computation compared to a normal neural network • The same knowledge is used in all image locations	• Requires a lot of training data samples • Difficulty to classify images with various positions • Tend to be much slower due to operations like maxpool • Very often requires a machine with a very good Graphics Processing Units (GPU)

multiple sensors to obtain the processing signals. The EMD transformation decomposes these signals. The indicators of the decomposed signals are calculated by performing a combination of multi-sensor features. They are using an SVM as a classification model, an identification model with one of the best results (95.56% accuracy) to identify the chatter. Table 9 shows the advantages and disadvantages of these methods.

Table 10 presents the list of the ten articles with the best accuracy values.

It is important to note that in all these publications, the chatter phenomena are associated with an increase in amplitude vibrational signal and that most verification experiments are far from industrial applications.

3.2.2 Deep learning

As the input dimension grows, machine learning models quickly get stuck by many local minima or fail to converge in good time. These limitations necessitate human expertise in feature extraction to reduce the dimension of the original signal inputs with statistical methods. Despite the success of manual feature extraction techniques for machine learning models in several problems, they have some drawbacks like (1) the extracted features that are specific and not generalized to solve different problems, and (2) the whole set of extracted features that is a partial representation, instead of a complete representation of the original signal. (3) The classification model, trained on partial features, represents a non-partial relationship between features and machining states rather than the beneficial relationship between signal and machining states [102].

This stage of human expertise for feature extraction aims to reduce the dimension of the input. Artificial intelligence advancements have allowed techniques such as deep learning to extract features directly as input data (Fig. 1).

One of the most common methods is the Convolutional Neural Network (CNN), which has become a popular technique for transforming data into information due to its ability to process raw data and automatically recognize representations of data features across multiple abstractions [103]. The document [104] built a deep learning model to detect chatter using the vibration signal converted to the time–frequency spectrum as input. The deep neural network extracts the time–frequency features, and the vibration signal is then decomposed into the chatter band by the VMD. An SVM is introduced to classify

Table 10 The ten articles with the best performance in chatter detection

Literature	Pretreatment	Learning models	Process	Precision (%)
[91]	WT	MLP	Milling	94
[45]	WT	SVM	Turning	95
[61]	EMD	SVM	Turning	95
[93]	WT	SVM		95
[57]	-	MLP-RBF	Milling	97
[62]	WPT	SVM	Milling	95
[99]	TDA	LRC	Turning	97
[100]	WPT-FFT-SSA	SVM	Milling	96
[96]	VMD	SVM	Milling	92.59
[98]	WPT	SVM	Milling	96.66
[101]	DTW	KNN	Turning	98
[26]	WPT	SVM	Turning	95

the features extracted from the chatter detection. The authors of the document [105] used images of the inner surface of the bearing to detect bearing defects caused by vibration or chatter, but such a technique is not adapted to in situ monitoring. They transform the vibration signals into a time–frequency image using the continuous wavelet transform (CTW). Based on the CWT scalogram, the document [54] proposes a CNN-based methodology to detect chatter in a milling process. The recorded cutting force signals are imaged using CWT and then classified into three categories (stable, transit, and unstable). These images are introduced as input to the CNN for classification without the feature extraction process. A deep neural network is trained to detect the different phases of chatter. The authors of the document [68] managed to see chatter on the image of the machined part by mixing CNN and genetic algorithm and overcome the oscillation problem related to the use of genetic algorithms by optimizing their algorithm. The document [106] presents a chatter detection approach combining a convolutional neural network and a physics-based model. They use the convolutional neural network to simulate the functioning of the human brain by connecting virtual neurons with tuned weights resulting in a prediction of a state. An intelligent chatter detection model is proposed by the authors of the document [107] using CWT preprocessing and a deep convolutional neural network (DCNN). In the document [55], the authors combine AlexNet, a pre-trained deep neural network, and an analytical solution using transfer learning to detect chatter. Another type of Long Short-Term Memory (LTSM) neural network is proposed by the authors of the document [108] for detecting chatter based on the sequence of control currents. Table 11 lists the articles that achieved the best performance in chatter detection using either machine learning or deep learning.

In these relatively recent researches, many deep learning techniques have been tested, often mixed with other methods, and generally lead to good results. Most studies still use machining conditions far from industrial applications, but some publications use realistic cutting conditions. Unfortunately, it is always apparent that vibration amplitude is strongly related to chatter. It is difficult to determine if all these sophisticated techniques are better than simple RMS level monitoring.

Table 11 List of the top deep learning models with the best performance for chatter detection

Literature	Features extraction	Learning models	Process	Precision (%)
[86]	WT	CNN	Milling	99
[104]	VMD	CNN	-	92.57
[68]	–	CNN	Milling	98.8
[105]	CWT-CNN	CNN	Turning	99
[54]	CWT	CNN	Milling	99.67
[106]	STFT	CNN	Milling	98.90
[107]	CWT	DCNN	Milling	99.98
[55]	EMD	AlexNet	Milling	82–100
[108]	–	LSTM	Milling	98

4 Discussion and perspectives

Machining processes are accurately described from complex dynamic models containing non-linearities, delays, and stochastic effects. Regarding the nature of these models and the practical challenges that include temporal variables, the transition from the design (numerical and analytical forms) of machining to the vibration analysis of accurate cutting signals remains challenging. This study categorizes the different techniques for chattering detection using vibration signals in three stages. First are time–frequency processing or decomposition techniques, which decompose the signal into several fragments using a transformation method to obtain the relevant chatter information. Then the FFT, for example, is applied to the elements which overlap the chatter frequencies identified on the signal. These techniques require much analysis time from an expert, who visualizes these fragments to detect chatter. Several authors have used features extracted by transformation techniques as input data for machine learning classifiers to solve this problem. The features are labeled in the input–output format to train the classifier in order to recognize the different phases of the signal (chatter). Several major studies have demonstrated promising results in applying machine learning techniques to vibration signal analysis to detect, identify, stabilize, or suppress chatter (Table 10). These machine learning methods cannot handle high-dimensional data due to the limitation of modeling capability [109]. Unlike conventional machine learning methods, deep learning will automatically extract features at a higher level and merge feature extraction and classification into a single structure so that it does not require a lot of trial and error. Like machine learning models, deep learning has also improved chatter detection performance. Some authors achieve almost 100% accuracy using the transfer learning technique (Table 11). Despite the excellent ability of AI models to provide highly accurate predictions in vibration chatter detection, they still face some significant challenges: (a) the constraints on time and human expertise for labeling data, especially when the number of classes is high before training the model; (b) needs of significant computational resources during the learning and classification phases to dash; (c) the lack transparency due to their inherent black box natures.

- To alleviate the data labeling problem, one can either use the following options:

    - Semi-supervised learning that combines supervised and unsupervised learning. Unsupervised learning algorithms are used to automatically generate labels, which will then be fed into supervised learning algorithms. Semi-supervised learning has a significant advantage in reducing the cost of labeling large datasets. Unsupervised learning models can traverse high-dimensional data and distinguish groups or atypical data points in a data set. The features extracted by the different transformation techniques (WT, FFT, STFT, HHT) or decomposition techniques (EMD and EEMD) can be categorized by unsupervised techniques like KNN or K-means. The clusters obtained by these methods are considered classes and will serve as input data for a supervised learning model.
    - Topological data analysis (TDA) that allows information to be extracted from high-dimensional, incomplete, or noisy datasets. TDA makes it possible to combine algebraic topology with other mathematical tools to develop a study of purely mathematical form. One of the main tools of TDA is persistent homology which has attracted the attention of many researchers for topological signal analysis [97, 99]. The combination of TDA for data labeling and transfer learning for feature extraction can be a powerful tool for chatter detection.

- The computational resource problem during model training can be solved by high-performance computing platforms such as Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs) like Google's GPU collab, Azure Machine Learning, and Amazon Web Services.
- The artificial intelligence models currently used, mainly convolutional or deep neural networks, are so complex that it is almost impossible for their designer to understand their operation fully, hence the term black box. However, explaining their decisions can bring multiple benefits to a machinist. To clarify and explain this notion of the black box, the document [110] proposes the concept of explainable AI. While improving the performance of these models, explainable AI helps identify problems and flaws in datasets and model operation, allowing experts, data scientists, and users to understand and trust the models with their predictions, taking into account regulatory compliance.
- In these studies, the authors seek either to detect or suppress chattering. Since chatter affects part quality, performance, and cutting tool life, vibration can be mitigated by considering all these dynamic elements. Multimodal learning can be a solution to integrate during the design of chatter detection models that considers all the elements and their intrinsic characteristics, capacities, and limits and will significantly contribute to chatter detection. Multimodal fusion is one of the original themes of multimodal machine learning, with works in the literature favoring early, late, and hybrid fusion approaches. Technically, multimodal fusion integrates information from multiple modalities to predict an outcome of measurement: a category by classification or a continuous value by regression [111].
- To avoid chatter in cutting processes, one can think of developing an intelligent machine tool to detect, decide, and control the cutting conditions in order to guarantee the optimal machining operation. For this, reinforcement learning can use an algorithm allowing them to perform a task by giving them positive or negative cues as he works on how to complete the job. The reward rules are defined, letting the algorithm decide which steps to take to maximize its reward and accomplish the task.
- The placement of sensors in the cutting tool represents a progression in tool process monitoring, allowing users to collect the data necessary to create more accurate digital twins for machining processes. The authors have already explored this concept of intelligent machining by presenting four tools, including a cutting force-based smart tool, a cutting temperature-based cutting tool, a fast tool servo (FTS), and intelligent collets for ultra-precision. The document [112] introduces the concept of intelligent machining to minimize toolpaths and machining time, improve the surface quality of components, increase tool life, accurately machine specific complex structures, enable autonomous sensing with self-learning to improve process performance, and dynamically sense the cutting process. These technologies can be used to monitor the machining process and tool wear as one of the ways to solve the annoying chatter phenomenon.

In practice, the authors of document [113] experimented with an intelligent tool for a high-speed drilling operation on a multilayer Printed Circuit Board (PCB) part. First, it was demonstrated by measuring the axial displacement that the smart tool performs self-protection of the spindle during the experiment. The intelligent tool detects the wear of the drilling tool, especially the most severe ones, which start at the periphery of the tool and decrease progressively toward the center since the outer primary cutting edge is subjected to the highest torque than its adjacent ones. This means that the quality of the hole depends on the number of holes drilled.

5 Conclusion

In this paper, we provide a mapping analysis of the different chatter detection techniques, from the time–frequency signal processing method and decomposition to the application of artificial intelligence for automatic detection. This cartographic analysis allowed us to visualize the most significant articles, the most cited authors, the collaboration between authors, the most productive countries, continents, and journals, the partnership between countries, the authors' keywords, and the research trends on chatter detection. This analysis showed the limitations of classical time–frequency signal processing techniques in explaining the value of applying AI for feature extraction and decision-making. A comparison between the different processing techniques has been established in Table 8, showing the use of the main principles of each method. Despite the growth of AI (machine learning and deep learning) in various fields, traditional signal processing techniques continue to complement AI models in chatter detection. Researchers do not often use AI techniques to detect chatter phenomena compared to other areas. In this analysis**,** 679 papers were collected, but only 75 articles involved the application of the different machine learning or deep learning methods, whose global citations are presented in Table 7. We have also discussed the limitations of the other AI techniques and proposed solutions to mitigate the problems of extensive data, the cost of computation time, and the lack of transparency of these models, which significantly hinder its use in such traditional fields as machining. These solutions can allow implementation of a multimodal system to consider and link the elements that cause chatter and the development of an intelligent cutting tool using reinforcement learning. Finally, we propose using explainable AI algorithms to gain additional scientific knowledge on AI models and improve understanding of complex situations.

Declarations

Conflict of interest The authors declare no competing interests.

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