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A bibliometric analysis of off-line handwritten document analysis literature (1990–2020)

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A R T I C L E I N F O

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A B S T R A C T

Providing computers with the ability to process handwriting is both important and challenging, since many difficulties (e.g., different writing styles, alphabets, languages, etc.) need to be overcome for addressing a variety of problems (text recognition, signature verification, writer identification, word spotting, etc.). This paper reviews the growing literature on off-line handwritten document analysis over the last thirty years. A sample of 5389 articles is examined using bibliometric techniques. Using bibliometric techniques, this paper identifies (i) the most influential articles in the area, (ii) the most productive authors and their collaboration networks, (iii) the countries and institutions that have led research on the topic, (iv) the journals and conferences that have published most papers, and (v) the most relevant research topics (and their related tasks and methodologies) and their evolution over the years.

1. Introduction

Document image analysis deals with the automated extraction of information [1] from documents. It has important applications in numerous domains. According to their data source, document analysis systems are typically classified into *on-line*, where data are collected dynamically during the writing through some device (e.g., a tablet), and *off-line*, where data are gathered statically from document page images after a scanning process [2]. Besides, documents may include printed, handwritten and graphical elements.

This paper reviews the research literature on a type of document analysis called *off-line handwritten*, which is particularly challenging because it works with data that do not contain any dynamic information that usually helps on-line systems to process information [3] (e.g., writing velocity, pen liftings and pauses, writing pressure changes, sequence ordering of strokes, etc.). Also, handwritten text has much more variability than the printed one [4]; there is *interpersonal variability* because the same person's writing often accommodates different situations, and *interpersonal variability* due to the writing styles of people.

Our review encompasses, among others, the following off-line handwritten topics: *Handwritten Text Recognition* (HTR), *Signature Verification* (SV), *Writer Identification* (WI), *Word Spotting* (WS), *Information Retrieval* (IR), and *Script Identification* (SI). HTR [2] deals with the transcription of a handwritten input (paper documents, photos, etc.) into its symbolic representation. This problem often it is focused on *Handwritten Characters Recognition* (HCR), *Handwritten Numeral Recognition* (HNR), *Handwritten Word Recognition* (HWR), and/or *Handwritten Sentence/text line Recognition* (HSR). SV [5] decides whether a signature is genuine or a forgery. WI [6] tries to find the authorship of the document from a known list of authors. In this case, the authentication process is made by analyzing handwritten text. WS [7] creates keywords to index documents in repositories, while IR [8] looks for a specific element (e.g., keywords) as a result of a query in a repository search. Finally, SI [9] determines the alphabet(s) in which a text is written.

Since 1990, much research has been published on off-line handwritten document analysis. To assist practitioners and researchers in finding the most prominent articles, authors, research trends, and near-future challenges, this paper examines a total of 5389 articles published from 1990 to December 2020. For such purpose, two bibliometric techniques were used: performance analysis and science mapping. *Performance analysis* [10] measures impact by counting citations; it can be applied to estimate the perfor-

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```
1 TITLE(
2   (hand-writ* OR handwrit* OR hand-print* OR handprint*)
3   AND (recognition  OR  verification  OR  spotting  OR  identification  OR
4       analysis  OR  segmentation)
5   AND NOT( (on-line OR online) AND NOT(off-line OR offline) )
6 ) AND (
7   LIMIT-TO(SUBJAREA, "COMP") OR LIMIT-TO(SUBJAREA, "ENGI") OR
8   LIMIT-TO(SUBJAREA, "MATH")
9 )
```

Fig. 1. Query used to retrieve from Elsevier Scopus the publication sample this article analyzes.

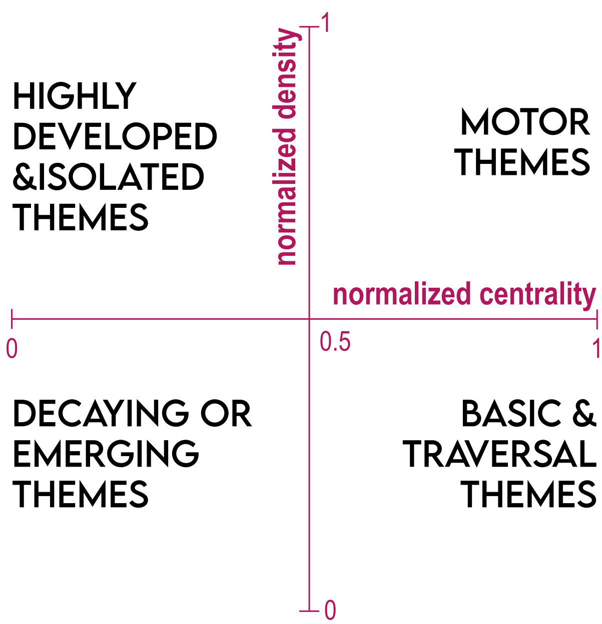

Fig. 2. TN roles according to the strategic diagram quadrants.

mance of authors, institutions, articles, journals, etc. *Science mapping* [11] identifies the most researched topics, related tasks and methodologies, measuring their influence over time using graph theory and clustering algorithms. In particular, this paper answers the following research questions:

1. What articles are the most influential?
2. Which authors and institutions have relevant research on off-line handwritten document analysis?
3. Which journals and conferences have published the largest number of articles?
4. Which problems have been the most studied on off-line handwritten document analysis?
5. What techniques have been used to face those problems?
6. How has the interest in the main research topics evolved over the years? Where will research be focused on the short-term future?

The rest of this paper is organized as follows. Section 2 summarizes related work. Section 3 describes the methodology we have followed for our bibliometric analysis. Section 4 reports and discusses the achieved results. Finally, some concluding remarks are provided in Section 5.

2. Related work

As far as we know, this paper is the first attempt to provide a global bibliometric overview of off-line handwritten document analysis. No previous work has considered so many articles, nor has approached the study using bibliometric techniques. This section summarizes other review articles that targeted more specific scopes.

First, we should highlight the classic reviews published by Mori et al. [12], Plamondon and Srihari [2], Arica and Yarman-Vural [13], Vinciarelli [14], Koerich et al. [15], Bunke [16], and Rehman and Saba [17].

Document analysis systems are often structured in five stages: pre-processing, segmentation, feature extraction, modeling, and post-processing [2]. Several reviews are specifically focused on some of these stages. For example, [18] covers literature on pre-processing, [19] on segmentation, [20] on feature extraction, and [21] modeling techniques.

WI is a very close problem to handwriting recognition, and some articles review both [2]. Others are focused on WI and writer verification [22].

In SV, some influential reviews are Plamondon and Lorette [23] and Impedovo and Pirlo [24].

WS and IR have been reviewed by Giotis et al. [25] and Doermann et al. [8], respectively.

Several studies are *script-specific*, such as Arabic [26], Indian [27], and Chinese [28]. As SI is also an important task in multi-language systems, some authors have reviewed this particular problem [9].

3. Materials and methods

This section explains how bibliographic data was retrieved and processed. Moreover, it describes the two bibliometric techniques used in this paper: performance analysis and science mapping.

3.1. Bibliometric workflow

To perform our analysis systematically, we followed the workflow recommended by Cobo et al. [29], PRISMA [30], and Börner et al. [31], which is structured in three phases:

1. *Data retrieval.* As pointed by Wohlin et al. [32], gathering the whole population of articles that fall into the scope of a bibliometric analysis is unrealistic. Consequently, we sought the more pragmatic goal of getting an unbiased publication sample representing the population satisfactorily.
   Several studies [33,34] have shown that Clarivate Analytics-Web of Science (WoS) and Elsevier Scopus provide the highest-quality bibliographic data for longitudinal analyses. Hence, we checked the WoS and Scopus coverture for our analysis scope, finding that Scopus roughly provides a superset of the bibliographic records given by WoS, including some more documents published in conference proceedings. It is worth noting that citation counts vary considerably among databases, so mixing records from different databases produces inconsistent counts [34,35]. Therefore, we decided to use Scopus as the only data source for our sample.
   A database query was refined iteratively until a convenient balance between completeness and absence of false positives was accomplished. Fig. 1 shows the final query. Line 2 looks for documents whose title includes handwriting documents (`hand-writ*`, `handwrit*`, etc.). The truncation symbol * captures all possible endings a word may

Table 1
Citation classics (the *h*-index is 93).

Paper	Journal/Conf.	#Cit	Topic
Plamondon and Srihari [2]. On-line and off-line handwriting recognition: A comprehensive survey (2000)	IEEE T Pattern Anal	1749	HTR, SV, Survey
Xu et al. [45]. Methods of combining multiple classifiers and their applications to handwriting recognition (1992)	IEEE T Syst Man Cyb	1655	HNR
Hull [46]. A database for handwritten text recognition research (1994)	IEEE T Pattern Anal	1029	HTR, Database
Graves et al. [4]. A novel connectionist system for unconstrained handwriting recognition (2009)	IEEE T Pattern Anal	982	HWR
Marti and Bunke [47]. The IAM-database: An English sentence database for offline handwriting recognition (2003)	Int J Doc Anal Recog	588	HTR, Database
Graves and Schmidhuber [48]. Offline handwriting recognition with multidimensional recurrent neural networks (2009)	NeurIPS	522	HWR
Huang and Suen [49]. A method of combining multiple experts for the recognition of unconstrained handwritten numerals (1995)	IEEE T Pattern Anal	418	HNR
Liu et al. [50]. Handwritten digit recognition: Benchmarking of state-of-the-art techniques (2003)	Pattern Recogn	401	HNR
Lorigo and Govindaraju [26]. Offline Arabic handwriting recognition: A survey (2006)	IEEE T Pattern Anal	342	HTR, Survey
Marti and Bunke [51]. Using a statistical language model to improve the performance of an HMM-based cursive handwriting recognition system (2001)	Int J Pattern Recogn	314	HSR
Suen et al. [52]. Computer recognition of unconstrained handwritten numerals (1992)	Proc IEEE	300	HNR
Arica and Yarman-Vural [13]. An overview of character recognition focused on off-line handwriting (2001)	IEEE T Syst Man Cy C	291	HCR, Survey
Said et al. [53]. Personal identification based on handwriting (2000)	Pattern Recogn	246	WI
Pham et al. [54]. Dropout improves recurrent neural networks for handwriting recognition (2014)	ICFHR	239	HWR
Liu et al. [55]. Handwritten digit recognition: Investigation of normalization and feature extraction techniques (2004)	Pattern Recogn	226	HNR
Bhattacharya and Chaudhuri [56]. Handwritten numeral databases of Indian scripts and multistage recognition of mixed numerals (2009)	IEEE T Pattern Anal	210	HNR, Database
Kimura et al. [57]. Handwritten numerical recognition based on multiple algorithms (1991)	Pattern Recogn	203	HNR
Vinciarelli et al. [58]. Offline recognition of unconstrained handwritten texts using HMMs and statistical language models (2004)	IEEE T Pattern Anal	201	HWR
Lauer et al. [59]. A trainable feature extractor for handwritten digit recognition (2007)	Pattern Recogn	194	HNR
Kim and Govindaraju [60]. A lexicon driven approach to handwritten word recognition for real-time applications (1997)	IEEE T Pattern Anal	189	HWR
Fischer et al. [61]. Lexicon-free handwritten word spotting using character HMMs (2012)	Pattern Recogn Lett	186	WS
Madhvanath and Govindaraju [62]. The role of holistic paradigms in handwritten word recognition (2001)	IEEE T Pattern Anal	177	HWR
Kato [63]. A handwritten character recognition system using directional element feature and asymmetric mahalanobis distance (1999)	IEEE T Pattern Anal	177	HCR
Manmatha et al. [64]. Word spotting: a new approach to indexing handwriting (1996)	CVPR	176	WS
El-Yacoubi et al. [65]. An HMM-based approach for off-line unconstrained handwritten word modeling and recognition (1999)	IEEE T Pattern Anal	173	HWR
Chen et al. [66]. Offline handwritten word recognition using a hidden Markov model type stochastic network (1994)	IEEE T Pattern Anal	173	HWR
Senior and Robinson [67]. An off-line cursive handwriting recognition system (1998)	IEEE T Pattern Anal	172	HWR
Liu et al. [68]. Online and offline handwritten Chinese character recognition: Benchmarking on new databases (2013)	Pattern Recogn	169	HCR
España-Boquera et al. [69]. Improving offline handwritten text recognition with hybrid HMM/ANN models (2011)	IEEE T Pattern Anal	168	HWR
Oliveira et al. [70]. Automatic recognition of handwritten numerical strings: A Recognition and Verification strategy (2002)	IEEE T Pattern Anal	165	HNR
Zhong et al. [71]. High performance offline handwritten Chinese character recognition using GoogLeNet and directional feature maps (2015)	ICDAR	158	HCR
Lavrenko et al. [72]. Holistic Word Recognition for Handwritten Historical Documents (2004)	DIAL	155	HWR
Marti and Bunke [73]. A full English sentence database for off-line handwriting recognition (1999)	ICDAR	154	HTR, Database
Zheng and Doermann [74]. Machine printed text and handwriting identification in noisy document images (2004)	IEEE T Pattern Anal	142	WI
Plötz and Fink [21]. Markov models for offline handwriting recognition: A survey (2009)	Int J Doc Anal Recog	141	HWR, Survey
Adankon and Cheriet [75]. Model selection for the LS-SVM. Application to handwriting recognition (2009)	Pattern Recogn	140	HNR
Fukushima and Wake [76]. Handwritten Alphanumeric Character Recognition by the Neocognitron (1991)	IEEE T Neural Netwo	140	HCR
Louloudis et al. [77]. Text line and word segmentation of handwritten documents (2009)	Pattern Recogn	138	HWR
Rodríghez-Serrano and Perronnin [78].Handwritten word-spotting using hidden Markov models and universal vocabularies (2009)	Pattern Recogn	136	WS
C.L Liu et al. [79]. Lexicon-driven segmentation and recognition of handwritten character strings for Japanese address reading (2002)	IEEE T Pattern Anal	134	HSR
Ha and Bunke [80]. Off-line, handwritten numeral recognition by perturbation method (1997)	IEEE T Pattern Anal	133	HNR
Zhang et al. [81]. Online and offline handwritten Chinese character recognition: A comprehensive study and new benchmark (2017)	Pattern Recogn	132	HCR
Li et al. [82]. Script-independent text line segmentation in freestyle handwritten documents (2008)	IEEE T Pattern Anal	132	HSR
Jain and Zongker [83]. Representation and recognition of handwritten digits using deformable templates (1997)	IEEE T Pattern Ana	132	HNR
Shi et al. [84]. Handwritten numeral recognition using gradient and curvature of gray scale image (2002)	Pattern Recogn	130	HNR
Chacko et al. [85]. Handwritten character recognition using wavelet energy and extreme learning machine (2012)	Int J Mach Learn Cyb	126	HCR
Kimura et al. [86]. Improvement of handwritten Japanese character recognition using weighted direction code histogram (1997)	Pattern Recogn	126	HCR
Hildebrant and Liu [87]. Optical recognition of handwritten Chinese characters: Advances since 1980 (1993)	Pattern Recogn	126	HCR, Survey
Lu and Shridhar [88]. Character segmentation in handwritten words - An overview (1996)	Pattern Recogn	124	HWR, Survey
Wunsch and Laine [89]. Wavelet descriptors for multiresolution recognition of handprinted characters (1995)	Pattern Recogn	123	HCR

(*continued on next page*)

Table 1 (*continued*)

Paper	Journal/Conf.	#Cit	Topic
El-Hajj et al. [90]. Arabic handwriting recognition using baseline dependant features and hidden Markov modeling (2005)	ICDAR	122	HWR
Lee [91]. Off-line recognition of totally unconstrained handwritten numerals using multilayer cluster neural network (1996)	IEEE T Pattern Anal	122	HNR
Yamada et al. [92]. A nonlinear normalization method for handprinted kanji character recognition-line density equalization (1990)	Pattern Recogn	121	HCR
Koerich et al. [15]. Large vocabulary off-line handwriting recognition: A survey (2003)	Pattern Anal Appl	119	HWR, Survey
Pal et al. [93]. Handwritten numeral recognition of six popular Indian scripts (2007)	ICDAR	118	HNR
Bunke et al. [16]. Recognition of cursive roman handwriting - past, present and future (2003)	ICDAR	118	HTR, Survey
Chen and Wang [94]. Segmentation of single- or multiple-touching handwritten numeral string using background and foreground analysis (2000)	IEEE T Pattern Anal	118	HNR
Guerbai et al. [95]. The effective use of the one-class SVM classifier for handwritten signature verification based on writer-independent parameters (2015)	Pattern Recogn	117	SV
Mohamed and Gader [96]. Handwritten word recognition using segmentation-free hidden Markov modeling and segmentation-based dynamic programming techniques (1996)	IEEE T Pattern Anal	117	HWR
Liu et al. [97]. ICDAR 2011 Chinese handwriting recognition competition (2011)	ICDAR	113	HTR
Al-HajjMohamad et al. [98]. Combining slanted-frame classifiers for improved HMM-based Arabic handwriting recognition (2009)	IEEE T Pattern Anal	113	HWR
Liu and Nakagawa [99]. Evaluation of prototype learning algorithms for nearest-neighbor classifier in application to handwritten character recognition (2001)	Pattern Recogn	112	HCR
Arica and Yarman-Vural [100]. Optical character recognition for cursive handwriting (2002)	IEEE T Pattern Anal	111	HWR
Knerr et al. [101]. Handwritten Digit Recognition by Neural Networks with Single-Layer Training (1992)	IEEE T Neural Networks	111	HNR
Pal and Datta [102]. Segmentation of Bangla unconstrained handwritten text (2003)	ICDAR	109	HTR
Cao et al. [103]. Recognition of handwritten numerals with multiple features and multistage classifiers (1995)	Pattern Recogn	108	HNR
Papavassiliou et al. [104]. Handwritten document image segmentation into text lines and words (2010)	Pattern Recogn	106	HSR
Sudholt and Fink [105]. PHOCNet: A deep convolutional neural network for word spotting in handwritten documents (2016)	ICFHR	106	WS
Yin and Liu [106]. Handwritten Chinese text line segmentation by clustering with distance metric learning (2009)	Pattern Recogn	106	HTR
Liu [107]. Normalization-cooperated gradient feature extraction for handwritten character recognition (2007)	IEEE T Pattern Anal	105	HCR
Revow et al. [108]. Using generative models for handwritten digit recognition (1996)	IEEE T Pattern Anal	105	HNR
Pechwitz and Maergner [109]. HMM based approach for handwritten Arabic word recognition using the IFN/ENIT-database (2003)	ICDAR	104	HWR
Heutte et al. [110].A structural/statistical feature based vector for handwritten character recognition (1998)	Pattern Recogn	104	HCR
Salah et al. [111]. A selective attention-based method for visual pattern recognition with application to handwritten digit recognition and face recognition (2002)	IEEE T Pattern Anal	102	HNR
Wang et al. [112]. Handwritten Chinese text recognition by integrating multiple contexts (2012)	IEEE T Pattern Anal	101	HTR
Stamatopoulos et al. [113]. ICDAR 2013 handwriting segmentation contest (2013)	ICDAR	100	HTR
Yin et al., [114]. ICDAR 2013 Chinese handwriting recognition competition (2013)	ICDAR	100	HCR
Su et al. [115]. Off-line recognition of realistic Chinese handwriting using segmentation-free strategy (2009)	Pattern Recogn	100	HSR
He et al. [116]. Writer identification of Chinese handwriting documents using hidden Markov tree model (2008)	Pattern Recogn	100	WI
Su et al. [117]. Corpus-based HIT-MW database for offline recognition of general-purpose Chinese handwritten text (2007)	Int J Doc Anal Recog	100	HTR, Database
Seni and Cohen [118]. External word segmentation of off-line handwritten text lines (1994)	Pattern Recogn	99	HWR
Si Wei Lu et al. [119]. Hierarchical attributed graph representation and recognition of handwritten chinese characters (1991)	Pattern Recogn	99	HCR
Hafemann et al. [120]. Learning features for offline handwritten signature verification using deep convolutional neural networks (2017)	Pattern Recogn	98	SV
Toselli et al. [121]. Integrated handwriting recognition and interpretation using finite-state models (2003)	Int J Pattern Recogn	98	HSR
Oliveira et al. [122]. A methodology for feature selection using multiobjective genetic algorithms for handwritten digit string recognition (2003)	Int J Pattern Recogn	98	HNR
Dehghan et al. [123]. Handwritten Farsi(Arabic) word recognition: A holistic approach using discrete HMM (2001)	Pattern Recogn	98	HWR
Gader et al. [124]. Handwritten word recognition with character and inter-character neural networks (1997)	IEEE T syst Man Cyb B	98	HWR
Van Breukelen et al. [125]. Handwritten digit recognition by combined classifier (1998)	Kybernetika	96	HNR
Favata and Srikantan [126]. A multiple feature/resolution approach to handprinted digit and character recognition (1996)	Int J Imag syst Tech	96	HCR
Chi et al. [127]. Handwritten numeral recognition using self-organizing maps and fuzzy rules (1995)	Pattern Recogn	95	HNR
H. Liu and Ding. [128]. Handwritten character recognition using gradient feature and quadratic classifier with multiple discrimination schemes (2005)	ICDAR	94	HCR
Liu et al. [129]. Discriminative learning quadratic discriminant function for handwriting recognition (2004)	IEEE T Neural Networks	93	HNR
Al-Ohali et al. [130]. Databases for recognition of handwritten Arabic cheques (2003)	Pattern Recogn	93	HTR, Database

have (e.g., `handwrit*` means any word that starts with `handwrit`). Lines 3 and 4 look for problems related to them (`recognition or verification or spotting or identification or analysis or segmentation`). Line 5 filters false positives. Lines 7 and 8 limit the subject area to computer science (`''COMP''`), engineering (`''ENGI''`), and mathematics (`''MATH''`).

The query was executed on Scopus on 19 December 2020. After filtering articles published between 1990 and 2020, 5389 records articles focused on off-line handwriting were achieved.

2. *Data cleaning and standardization*. Bibliographic data sometimes involves typographical errors and ambiguities that need to be corrected [11,29,36]. For instance, in our sample, "Á. Sánchez", "A. Sanchez", and "A. Sánchez" are slightly different versions of the same author's name. Moreover, as we will see in Section 3.3, our analysis is built upon a bibliometric technique that processes keywords. Unfortunately, neither most journals/conferences impose a set of standardized keywords, nor there is a thesaurus specific for "off-line handwritten document analysis". Accordingly, keywords were manually standardized. For example, in the context of our study, the following keywords: "NN", "Neural network classifier", "ANN", etc. correspond to the same concept, and thus they were grouped as "NN". It is true that grouping keywords by hand needs a thorough knowledge of the research area under analysis. To mitigate this subjectivity, keyword normalization was undertaken consensually. A public repository accompanying this paper provides all the details of our analysis (see Section 3.4). In particular, the repository reports the standardization of the author names and keywords exhaustively.
   To perform the longitudinal analysis of the research area, the paper sample was divided into six sub-periods of approximately five years each: 1990–1994, 1995–1999, 2000–2004, 2005–2009, 2010–2014, and 2015–2020, respectively. Moreover, 1726 documents did not include any keyword at all, and thus they were discarded for this analysis.
3. *Data analysis*. Using well-established bibliometric procedures, *performance analysis* and *science mapping* [37], the standardized data are analyzed.

3.2. Performance analysis

Research performance is typically measured through *citation analysis* [10], being the *h*-index the most commonly accepted citation analysis indicator [38]. This index can quantify the productivity of various bibliographic aspects: authors, journals, research areas, etc. For instance, the *h*-index of a research area is defined as follows [39]: A research area has index h whenever h of the n papers framed into the area have at least h citations each, and the remaining $n-h$ papers have less than or equal to h citations each.

3.3. Science mapping

The following sections explain the methods we used to identify the key research topics, tasks and methodologies, and their evolving relevancy over time. These methods analyze the standardized keywords of all papers in the sample and are supported by the open-source software SciMAT[1] [29].

3.3.1. Thematic network identification

The essential topics, tasks and methodologies, of a research area can be identified by building a *co-occurrence* graph, whose nodes refer to keywords, and whose edges are referred to *equivalence index* values [40]. The equivalence index between two keywords a and b is $e_{ab} = c_{ab}^2/c_a c_b$, where c_i is the number of documents that include the keyword i, and c_{ab} is the number of documents that contain both a and b. The range of e_{ab} goes from zero, when there is no document including both a and b, to one, when a and b cooccur in all documents.

Then, the most relevant topics, tasks and methodologies arise as clusters, known as *Thematic Networks* (TNs), of highly tied keywords according to their equivalence index (i.e., TNs are groups of standardized keywords that frequently appear together in the papers). In particular, we identify the clusters with the *simple centers*' algorithm [40], which has been applied successfully to numerous bibliometric analyses, e.g., [29,36,41].

3.3.2. Strategic diagrams and maps of conceptual evolution

The development of a research area can be examined by performing a longitudinal analysis as follows. First, the document sample is divided into periods, and the TNs for those periods are identified. Then, the role each network plays in a period is determined by Callon's *centrality* and *density* measures [40], which are based on the equivalence index. Specifically, on one hand centrality calculates the degree of interaction of a theme with the rest of them as $10 \cdot \sum_{a \in \text{network}, b \notin \text{network}} e_{ab}$. On the other hand density quantifies the network internal coherence as $\frac{100}{\#\text{network}} \cdot \sum_{a,b \in \text{network}} e_{ab}$.

Strategic diagrams [29] are helpful for visualizing network roles by placing the themes according to their *normalized* centrality and density. These normalized versions are obtained as $\text{rank}(c_t)/n$ and $\text{rank}(d_t)/n$, where $\text{rank}(c_t)$ and $\text{rank}(d_t)$ are the positions of the theme t in the centrality and density rankings sorted in ascending order, respectively; $\text{rank}(c_t)$ and $\text{rank}(d_t)$ are then divided by the total number of themes n to normalize their values into the interval $[0, 1]$. Fig. 2 shows the roles a TN may play according to the quadrant where it is placed in the strategic diagram. The theme movement across the quadrants over successive periods of years can be used to recognize the emergence and growth of research lines, and to forecast their short-term evolution [42].

Also, the comparison of each period keywords can reveal whether the number of researched topics, tasks and methodologies, increases (i.e., new words are incorporated), decreases (old words become obsolete), or remains stable. Following Sternitzke and Bergmann [43] recommendations, we use the *inclusion index* to track the evolution between two consecutive periods with keyword sets K and L: inclusion $\text{index}_{KL} = \frac{\#(K \cap L)}{\min(\#K, \#L)}$.

3.4. Material

Following *Open Science* good practices, this paper material is publicly available at: https://github.com/rheradio/offline-handwritten-doc-analysis

In particular, our repository provides:

1. The raw paper sample gathered from Scopus that this article analyzes.
2. The keywords' normalization.
3. The author names' standardization.
4. The SciMAT database we built to perform the bibliometric analysis.
5. A website reporting the results of our science mapping analysis exhaustively.

4. Results and discussion

This section outlines the most relevant results of our analysis. For a complete report, please check the repository linked in Section 3.4.

4.1. Most influential papers

This subsection identifies the most relevant papers for the whole period 1999–2020. To do so, we use the *citation classic* concept, which was coined by Garfield [44] to refer to the most impacting papers of a research area according to their number of citations.

In particular, we use the formal definition given by Martinez et al. [131], which is based on the *Hirsch index* [39]: "the citation classics, also called the *h-core*, of a research area whose *h*-index is

[1] https://sci2s.ugr.es/scimat/

Table 2
Hot papers: top 5 cited articles in 2020, 2019, and 2018.

Paper	Journal/Conf.	#Cit	Topic
Ghosh et al. [132]. Graphology based handwritten character analysis for human behaviour identification (2020)	CAAI T Intell Technol	35	Behaviour identification
Ahlawat et al. [133]. Improved handwritten digit recognition using convolutional neural networks (2020)	Sensors	19	HNR
Zhao and Liu [134]. Multiple classifiers fusion and CNN feature extraction for handwritten digits recognition (2020)	Granul Comput	18	HNR
Jiang and Zhang [135]. Edge-SiamNet and Edge-TripleNet: New deep learning models for handwritten numeral recognition (2020)	IEICE T Inf Syst	18	HNR
Malakar et al. [136]. A GA based hierarchical feature selection approach for handwritten word recognition (2020)	Neural Comput Appl	16	HWR
Diaz-Cabrera et al. [137]. A perspective analysis of handwritten signature technology (2019)	ACM Comput Surv	64	SV
Cilia et al. [138]. A ranking-based feature selection approach for handwritten character recognition (2019)	Pattern Recogn Lett	44	HCR, Feature Selection
De Stefano et al. [139] Handwriting analysis to support neurodegenerative diseases diagnosis: A review (2019)	Pattern Recogn Lett	31	Neurodegenerative diseases
Baldominos et al. [140]. A survey of handwritten character recognition with MNIST and EMNIST (2019)	Appl Sci	27	HCR
He and Schomaker [141]. Deep adaptive learning for writer identification based on single handwritten word images (2019)	Patter Recogn	24	WI
Hafemann et al. [142]. Offline handwritten signature verification - Literature review (2018)	IPTA	65	SV, Survey
Baldominos et al. [143]. Evolutionary convolutional neural networks: An application to handwriting recognition (2018)	Neurocomputing	57	HNR
Pramanik and Bag [144]. Shape decomposition-based handwritten compound character recognition for Bangla OCR (2018)	J Vis Commun Image R	53	HCR
Kulkarni and Rajendran [145]. Spiking neural networks for handwritten digit recognition-Supervised learning and network optimization (2018)	Neural Networks	49	HNR
Sueiras et al. [146]. Offline continuous handwriting recognition using sequence to sequence neural networks (2018)	Neurocomputing	46	HWR

h are the top h cited papers". In our paper sample, the h-index is 93 (there are 93 citation classics). Table 1 lists those top 93 citation classics. Columns stand for the paper title, publication source, number of citations, and central topic(s) of the paper.

As recent papers seldom have enough time to accumulate citations to compete with older articles, Clarivate WoS proposes recognizing as *hot papers* those with a number of citations beyond a given threshold. Accordingly, Table 2 shows the hot papers for the last three years, i.e., the top 5 cited articles per year.

4.2. Most prolific authors

A total of 8044 researchers have co-authored the 5389 papers that this article analyzes. Most of them are occasional authors; e.g., 69.87% have published a single paper. Only 7.13% of the researchers have published five or more papers. Such authorship distribution is coherent with a fundamental law in bibliometrics called *Lotka's law* [147], which states that the number of authors with n papers was habitually inversely proportional to n^2. In our case, 5621 researchers published only one paper; therefore, Lotka's law predicts that the number of authors that published n papers should be $5621/n^2$.

The graph in Fig. 3 depicts the collaboration patterns between the most productive researchers. Nodes represent the top 2.29% of authors, who have published at least ten papers; node areas are proportional to the number of published papers. There is an edge between two nodes if the corresponding researchers have co-authored one or more papers; the width of an edge connecting authors i and j is proportional to the equivalence index e_{ij} (this index was introduced in Section 3.3.1). Finally, the graph is colored according to the groups of collaborating authors identified with the Leiden algorithm [148].

4.3. Most prolific journals

Fig. 4 shows the journals that have published the largest number of papers, standing out *Pattern Recognition, Pattern Recognition Letters, IEEE Transactions on Pattern Analysis & Machine Intelligence*, and *International Journal on Document Analysis and Recognition* (which is specialized in document analysis). Likewise, Fig. 5 shows the most prolific conferences. Fig. 5 shows the most prolific conferences, including (i) those focused on off-line handwriting document analysis, such as the *International Conference on Document Analysis Recognition* (ICDAR) and the *International Conference on Frontiers of Handwriting Recognition* (ICFHR), and (ii) others with a more general thematic, such as the *International Conference on Pattern Recognition* (ICPR) or the *International Joint Conference on Neural Networks* (IJCNN).

4.4. Longitudinal analysis

Fig. 6 represents the number of published papers per year. Some significant developments have accelerated the upswing trend, such as the introduction of deep learning in 2006 [149], the 2009 NIPS Workshop on Deep Learning for Speech Recognition [150], and the popularization of inexpensive GPUs from 2012 onwards [151]. To analyze the temporal evolution of the area, we have divided the document sample into six periods of five years.

4.4.1. Most prolific research institutions and countries

Fig. 7 shows (i) the number of papers that researchers of each country have published, and (ii) the institutions to which researchers publishing the highest number of papers belong.

From 1990 to 1999, most research is concentrated in a few countries. USA, Japan, and Taiwan led the investigation, with 20.57%, 11.33%, and 8.13% of all published papers, respectively. In the next decade, from 2000 to 2019, research spread around the world. China and India emerged as global powers; in fact, the most prolific countries of that decade were China (18.41% of all published papers), USA (10.72%), and India (9.91%). Finally, in the last decade, India and China have consolidated their leadership with 28.80% and 17.42% of the articles; USA, Spain, and France follow them in the ranking with 6.01%, 5.33%, and 5.14% of the papers, respectively.

4.4.2. Thematic networks

As explained in Section 3.3, the science mapping technique that we have used to identify the most researched topics is based on

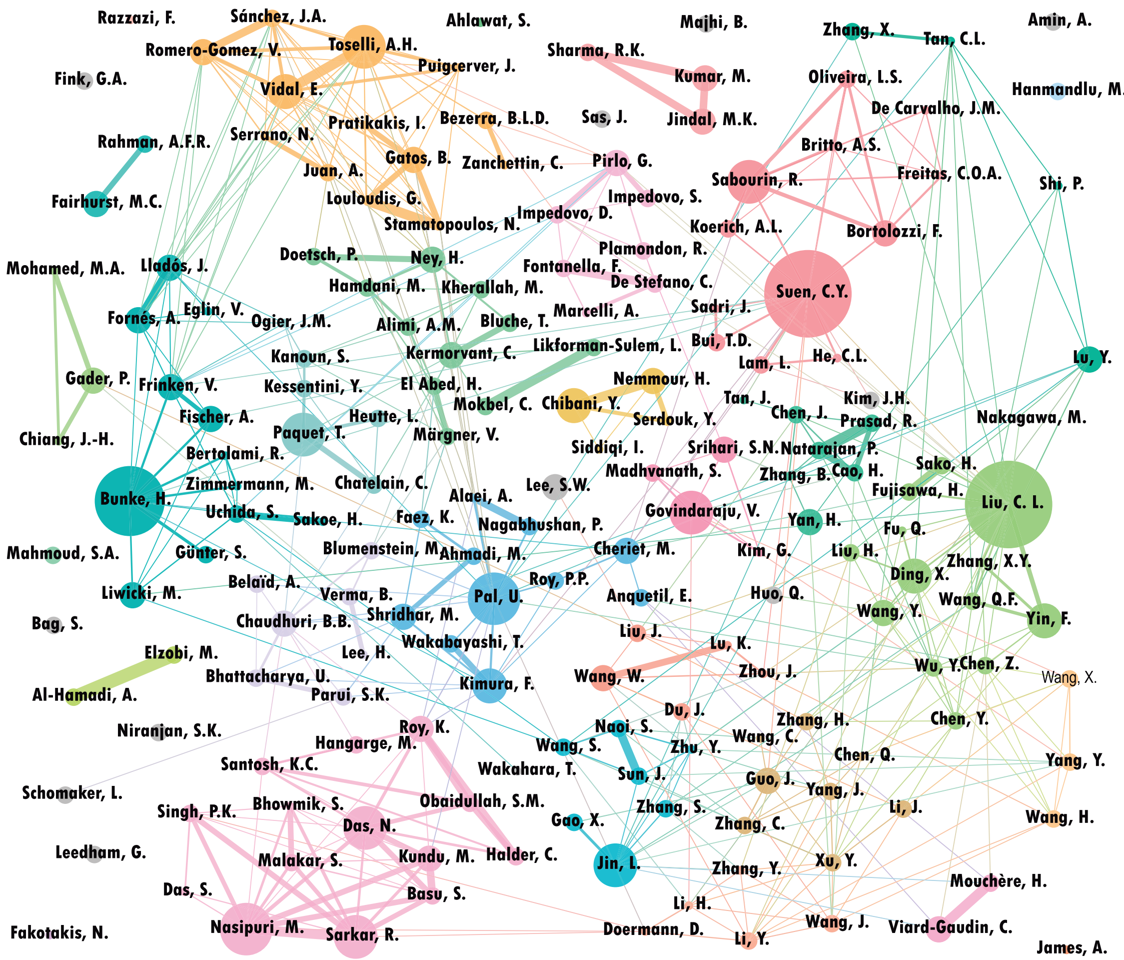

Fig. 3. Collaboration networks of the authors with ten or more papers.

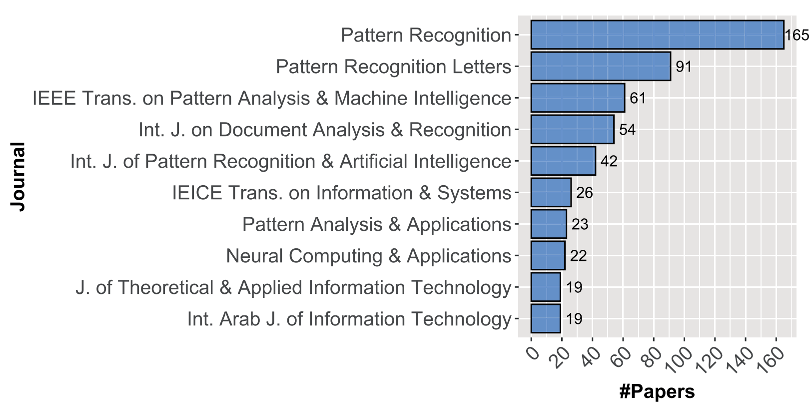

Fig. 4. Most prolific journals (1990–2020).

analyzing the relations between paper keywords. Fig. 8 represents the number of keywords evolution over time. Each node shows the number of keywords in a given period. Arrows connecting two nodes depict the number of shared keywords between two periods; the inclusion index is denoted in parentheses. Upper incoming arrows represent how many new keywords were added in a period, and upper outcoming arrows account for the keywords that became obsolete. For instance, the second period goes from 1995 to 1999; it comprises 74 keywords, 42 of them coming from the previous period. Out of these 74 keywords, 59 were used in the next period, and 15 were discarded. According to the inclusion index, 80% of this period's keywords were still used in the third period.

Using the simple centers' algorithm, sixteen TNs were identified. Some of them are related to document analysis problems:*Character Recognition*, *Text Recognition*, *Numeral Recognition*, *Chinese Character Recognition*, *Word Spotting*, *Writer Identification*, *Signature Verification*, *Script Identification*, and *Historical Text Recognition* (*Historical Documents*). Others refer to approaches for dealing with these problems: *Hidden Markov models (HMMs)*, *Support Vector Machine (SVM)*, *Deep Neural Networks (DNNs)*, *Ensemble Classification*, and *Attention Mechanism*; and the last ones are related to

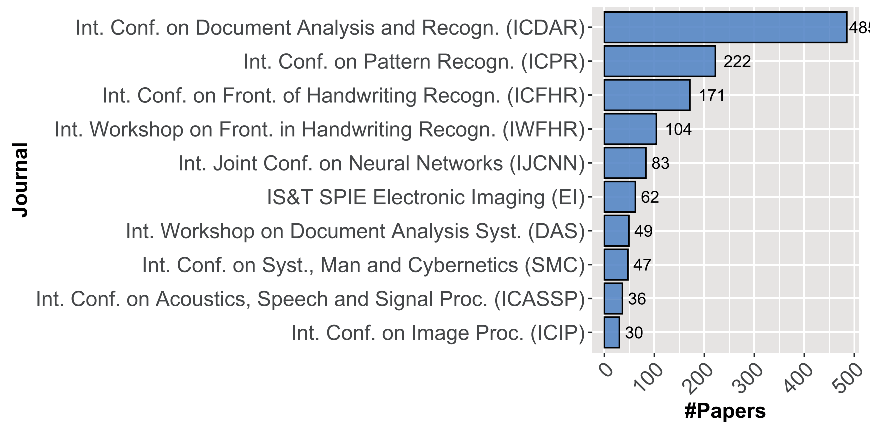

Fig. 5. Most prolific conferences (1990–2020).

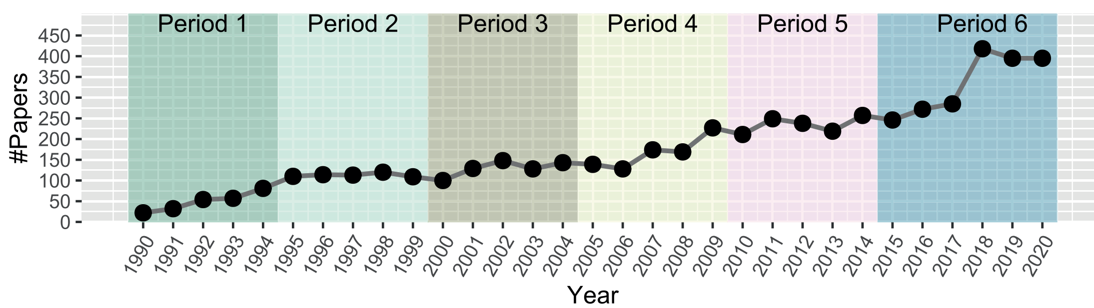

Fig. 6. Number of publications per year.

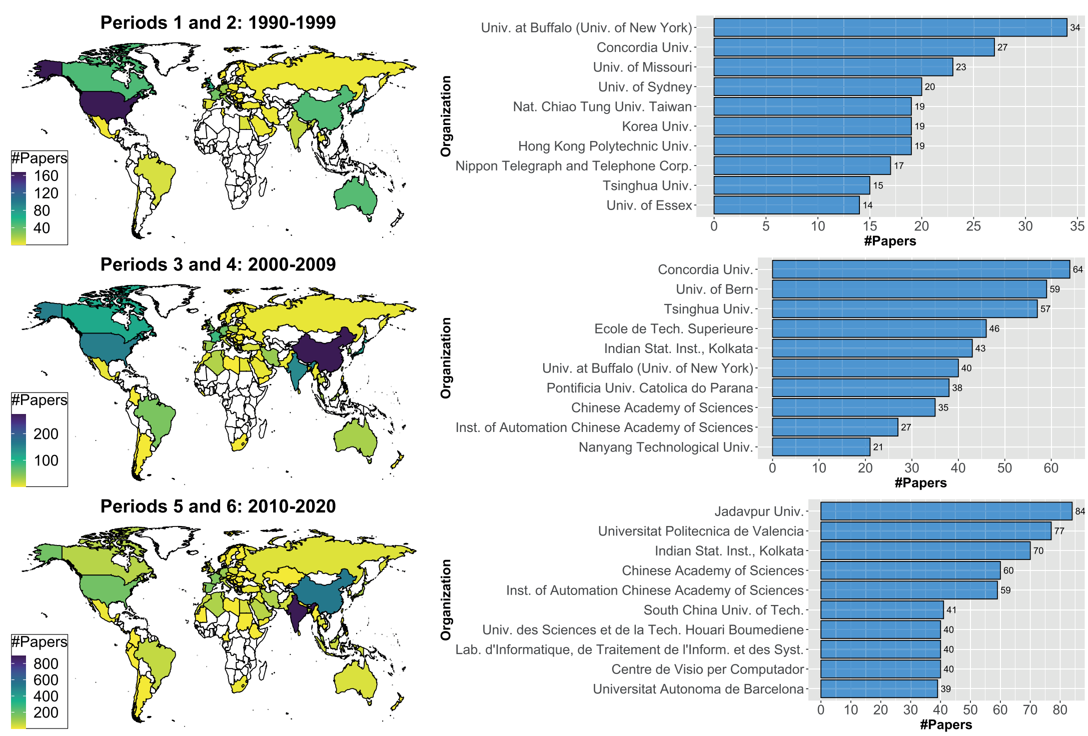

Fig. 7. Most prolific countries and organizations. The scale of the maps is related to the data volume in each period of time.

important tasks in the resolution of these problems (*Segmentation, Feature Extraction Classification*). Fig. 9 and the strategic diagrams in Fig. 10 provide the field evolution overview, which will be discussed in detail in the subsequent Sections 4.4.3–4.4.8.

In Figs. 9 and 10, each node represents a TN, being its size proportional to the number of papers using some of the keywords the network contains. Edges in Fig. 9 account for conceptual relations between TNs; a solid line connecting two TNs T and T' depicts a strong relationship, meaning that both TNs share a keyword that is central to some of them. A dashed line indicates the existence of some shared keywords between T and T', which is not central neither for T nor T'. For example, between the first and

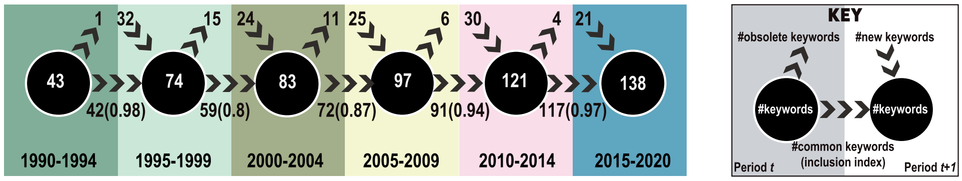

Fig. 8. Number of keywords per period.

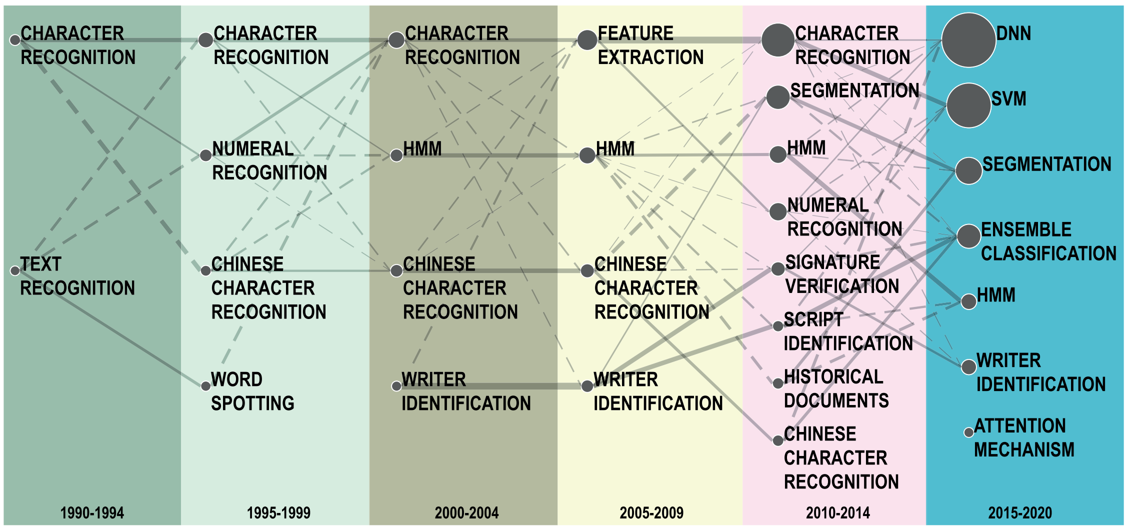

Fig. 9. TNs' conceptual linking between periods.

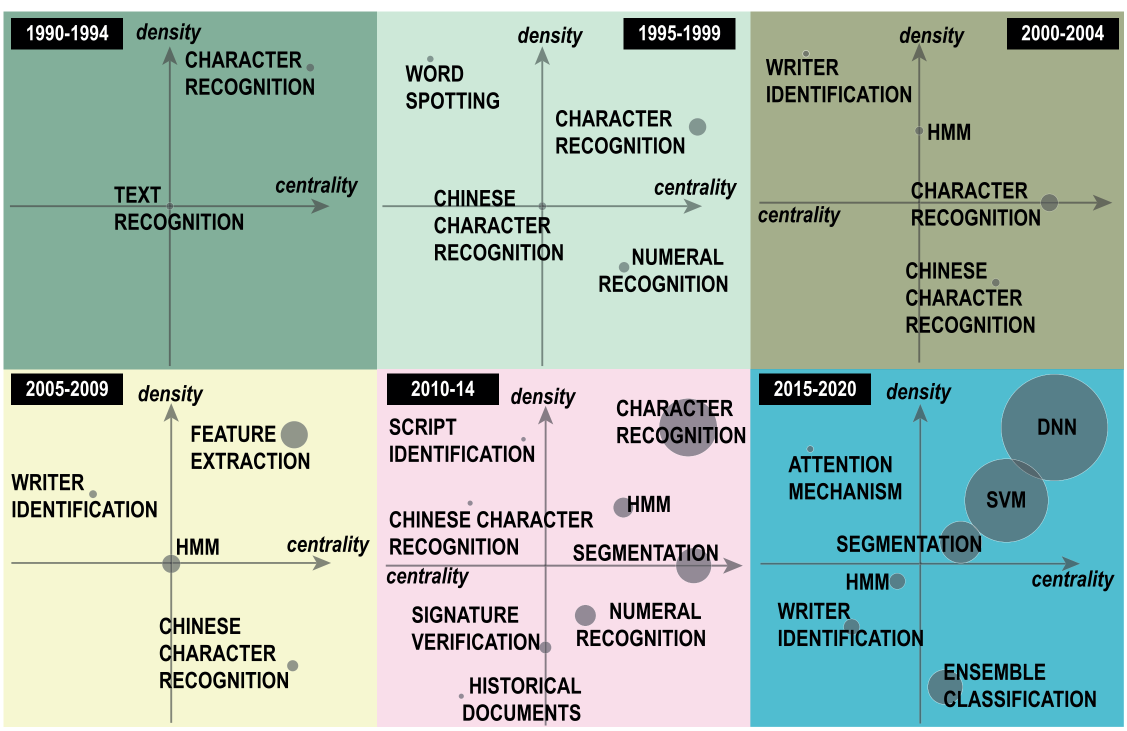

Fig. 10. Strategic diagrams per period.

second periods, (i) there is a solid line between *Character Recognition* and *Numeral Recognition*, because both themes share the keyword *Numeral Recognition*, which is central for the second one; and (ii) there is a dashed line between *Character Recognition* and *Chinese Character Recognition* because they share the non-central keywords *Graph* and *Preprocessing* (the keywords composing each TN and their interrelationships are provided in the repository linked in Section 3.4). Edge width is proportional to the inclusion index.

As explained in Section 3.3.2, the TN flow across the quadrants of successive strategic diagrams helps to recognize the emergence and growth of research lines and to forecast their short-term evolution. For example, according to Fig. 10, from 2005 to 2009 to

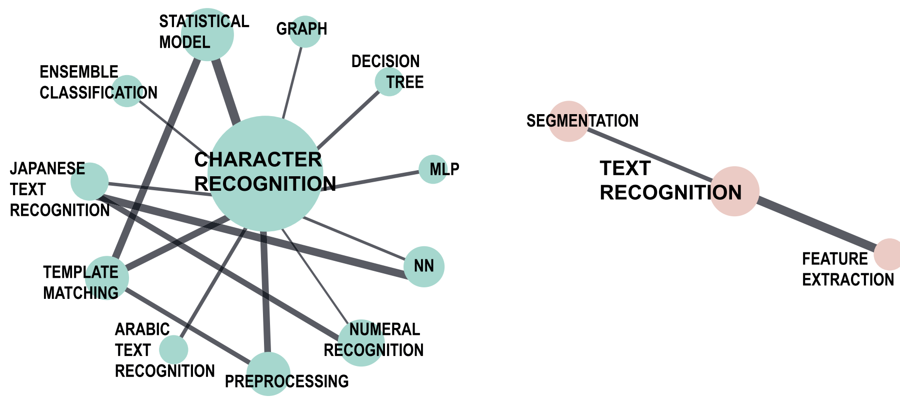

Fig. 11. Thematic networks for Period 1: 1990–1994.

2010–2020, *HMM* has increased both its centrality and its number of papers. Accordingly, it has become increasingly important, and it is reasonable to expect that, in the short-term future, the topics, tasks, and methodologies represented by the TN will be kept relevant. In contrast, Fig. 10 shows that *Chinese Character Recognition* has lost its centrality but increased its density from 2005 to 2009 to 2010–2014 period, evolving from being a traversal TN to a highly developed one.

The following subsections analyze the TNs in each period. For every network, a table summarizes the network's keywords, its number of articles, h-index, and the top 10 cited papers. This way, the relevancy a network has in a given period is quantified in terms of quantity (#papers) and quality (*h*-index). It is worth noting that a document may include keywords belonging to different TNs.

4.4.3. Period 1: 1990–1994

As Fig. 10 shows, two TNs are identified from 1990 to 1994: the motor network *Character Recognition* and the isolated one *Text Recognition*. Fig. 11 depicts the keywords' relationship for both TNs. Each node represents a standardized keyword (see Section 3.1) whose size depends on the number of articles that include it. An edge links two nodes if two or more articles contain the corresponding keywords. The edge thickness depends on the equivalence index that normalizes the number of articles where the keywords co-occur (see Section 3.3.1). It is worth noting that the simple centers' algorithm automatically labels the TN according to the most central keyword, i.e., to the keyword that is strongest connected to the other ones [40]. In Fig. 11, the most central keywords coincide with the most included in the articles, but this is not always the case. Also, a paper is considered to belong to the network if it contains at least one of the TN's keywords [29] (accordingly, not all articles in a TN necessarily include the keyword that gives its name).

Table 3 summarizes these networks' keywords and their top ten cited papers. The first column shows the central keywords that give names to the TNs; clicking on them, a browser will take you to a detailed TN description in our repository (see Section 3.4). The last column follows the notation $[\text{reference}]_{\#\text{citations}}$, e.g., $[52]_{300}$ means that [52] has been cited 300 times since its publication. On the one hand, HNR, Arabic and Japanese scripts were considered. Additionally, they were closely related to HCR problems. A highly influential paper on this TN and period is presented by Suen et al. [52], which combines four different heuristic methods proposed by experts for the unconstrained HNR problem. This technique is also known as ensemble classification. The authors demonstrated that the combination or consensus among the HNR methods tends to compensate for the weaknesses of individual algorithms while preserving their strengths. Therefore, ensemble classification became important in this and the following periods. Focusing on the keywords related to some methodology, Template Matching, Decision Trees, and Ensemble Classification were some of the most used strategies to solve these problems. Also, in these years, Neural Networks (NNs), in general, and the Multi-Layer Perceptron (MLP), in particular, started to be important since new optimization algorithms were developed and more effective training was possible. On the other hand, the *Text Recognition* TN encompassed the most studied tasks, which were Segmentation and Feature Extraction. Note that the keyword Text Recognition includes the keywords related to handwriting recognition that were not specific on any script or scope, such as characters, words, etc. Therefore, the keywords related to it are also generic. Concerning this second TN, the most cited paper was written by Hull [46]. It described an image database with thousands of city names, ZIP codes, and other types of words extracted from scanned post mail handwritten text and targeted towards general text recognition. The database was divided into explicit training and testing sets. The included words presented a high variability concerning writers and writing styles. Many of the applications and algorithms for HTR in that period were oriented towards postal address interpretation [152].

4.4.4. Period 2: 1995–1999

In this period, there were four TNs: the motor network *Character recognition*, the isolated network *Word Spotting*, and the traversal networks *Chinese Character Recognition* and *Numeral Recognition*. Fig. 12 and Table 4 summarize the keywords of these networks, showing that other motor TNs related to HCR were Character Segmentation, HWR, and Japanese text recognition. To solve these problems, HMMs were added to the previous motor methodologies. The first word recognition systems were based on character recognition and their subsequent concatenation. For that, HMMs were one of the most used ones. Therefore, it is natural that all these keywords appear together in this period. Moreover, the importance of these problems and techniques grew in the scientific community, as it is shown by the increase of its h-index. *Chinese Character Recognition* appears as its own TN, including related techniques as directional features and graph-based methodologies. *Numeral Recognition* was related to structural and ensemble classification, segmentation, clustering, fuzzy logic, K-Nearest Neighbour (KNN), and Genetic Algorithms (GA). Indeed, as HNR problems focused on isolated digits started to be solved, most numerical string recognition problems tried to segment digits to classify them. Then, digit string recognition was achieved by concatenating the previous results. Some of the most cited articles in this period belonged to this TN. The work by Huang and Suen [49] proposed a multiple classification approach for recognizing unconstrained

Table 3
TNs' performance for Period 1: 1990–1994.

TN	Network's keywords	#papers	h-index	Top 10 papers
Character Recognition	Character Recognition, Statistical Model, Graph, Decision Tree, MLP, NN, Numeral Recognition, Preprocessing, Arabic Text Recognition, Template Matching, Japanese Text Recognition, Ensemble Classification	44	22	[52]$_{300}$ [57]$_{203}$ [66]$_{173}$ [87]$_{126}$ [92]$_{121}$ [119]$_{99}$ [152]$_{80}$ [153]$_{78}$ [154]$_{71}$ [155]$_{51}$
Text Recognition	Text Recognition, Segmentation, Feature Extraction	14	11	[46]$_{1029}$ [118]$_{99}$ [152]$_{80}$ [156]$_{72}$ [157]$_{49}$ [158]$_{42}$ [159]$_{38}$ [160]$_{34}$ [161]$_{19}$ [162]$_{18}$

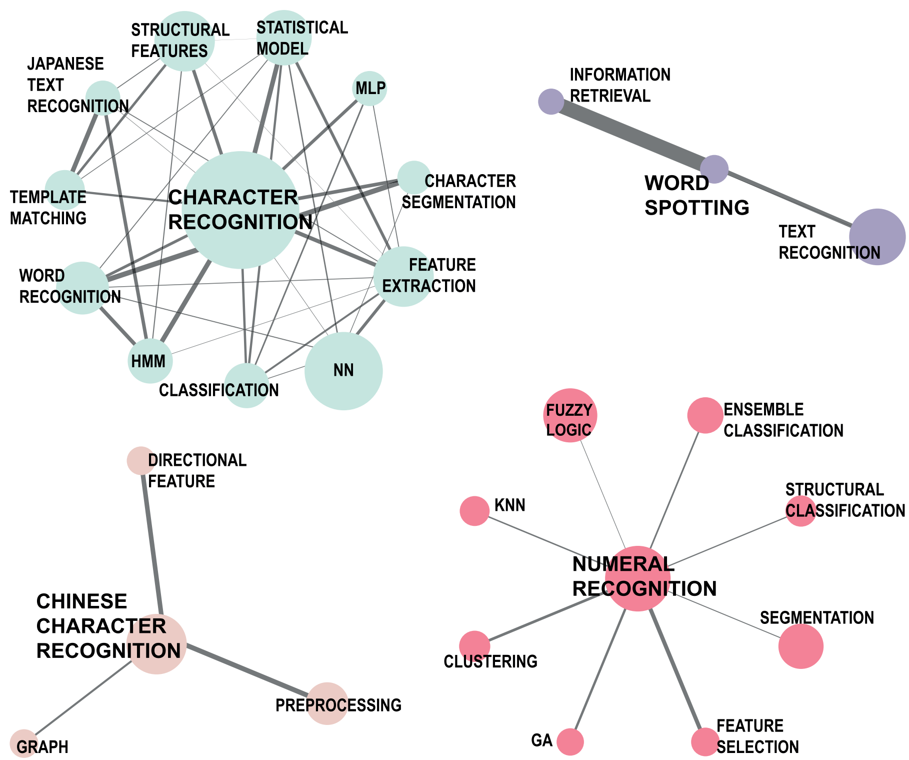

Fig. 12. Thematic networks for Period 2: 1995–1999.

handwriting numerals. Kim and Govindaraju [60] demonstrated the importance of using a lexicon for ranking the lexicon entries when matching them to word images in word recognition tasks suitable to real-time applications. Finally, Jain and Zongker [83] introduced the representation and usage of deformable templates to compute the deformation needed when comparing handwritten digit patterns for their recognition at a relatively low computational cost. *Word Spotting* was a new and very studied problem related to IR and HTR. Indeed, WS and IR were complementary tasks since WS tries to get keywords, and IR asks for specific keywords on documents. Moreover, HTR and WS share many common methodologies to address them. Also, a capital work was the gradient-based learning to train convolutional neural networks (CNNs) proposed by LeCun et al. [163]. Although this article is not devoted to handwritten documents (and for this reason, their literature is outside the sample), it was fundamental in computer vision studies, leading to a great development in many applications such as document analysis.

4.4.5. Period 3: 2000–2004

Fig. 13 and Table 5 summarize four TNs identified in this period. *HMM* was a motor and a highly studied TN. Indeed, in this period, the importance of word and sentence recognition problems, solved by HMMs approaches, increased. Besides, word recognition for large vocabulary problems was studied, especially using language models and dictionaries or lexicons to improve the results. Two relevant papers in the network correspond to the same authors Marti and Bunke ([51], and [47], respectively). Their first paper [51] described a solution that combines HMMs with statistical language models. The proposed solution avoids segmenting a text line into its constituent words and also incorporates linguistic knowledge into the recognition process. Their second paper [47] introduced the IAM database of English sentences for off-line handwriting recognition. This database has been (and still it is) a fundamental benchmark for training and testing many algorithms aiming to recognize handwriting text under multiple variabilities and also for performing WI. Meanwhile, *Character Recog-*

Table 4
TNs' performance for Period 2: 1995–1999.

TN	Network's keywords	#papers	h-index	Top 10 papers
Character Recognition	Character Recognition, Structural Features, Statistical Model, MLP, Character Segmentation, Feature Extraction, NN, Classification, HMM, Word Recognition, Template Matching, Japanese Text Recognition	162	37	[60]$_{189}$ [64]$_{176}$ [65]$_{173}$ [67]$_{172}$ [80]$_{133}$ [83]$_{132}$ [86]$_{126}$ [88]$_{124}$ [89]$_{123}$ [91]$_{122}$
Word Spotting	Word Spotting, Information Retrieval, Text Recognition	27	14	[49]$_{418}$ [64]$_{176}$ [73]$_{154}$ [164]$_{69}$ [165]$_{46}$ [166]$_{43}$ [167]$_{35}$ [168]$_{32}$ [169]$_{31}$ [170]$_{29}$
Chinese Character Recognition	Chinese Character Recognition, Directional Feature, Preprocessing, Graph	41	15	[63]$_{177}$ [65]$_{173}$ [67]$_{172}$ [83]$_{132}$ [86]$_{126}$ [171]$_{77}$ [172]$_{66}$ [173]$_{63}$ [174]$_{49}$ [175]$_{48}$
Numeral Recognition	Numeral Recognition, Ensemble Classification, Structural Classification, Segmentation, GA, Clustering, Fuzzy Logic, KNN, Feature Selection	86	31	[49]$_{418}$ [60]$_{189}$ [65]$_{173}$ [80]$_{133}$ [83]$_{132}$ [91]$_{122}$ [103]$_{108}$ [127]$_{95}$ [176]$_{78}$ [171]$_{77}$

nition, which was a motor and traversal TN, shows that HCR problems were studied using classical and new approaches (as self-organizing maps, SOMs). Methodologies such as principal component analysis (PCA), active shape models, SVM and GA were related to *Chinese Character Recognition*, which is based on a very different script compared to Roman (or Latin) or Arabic texts. In this TN, the work of C-L. Liu et al. [50] stands out, where state-of-the-art in HNR was benchmarked with their work, which combines different features as chain code and gradient features, with several classifiers as KNN, NN, and vector classifiers, among others. Other very studied but isolated topics were WI and SV, as they appear on the *Writer Identification* TN. Focusing on their impact through the paper production, the importance of the TNs *Character Recognition* and *Chinese Character Recognition* were increased. Finally, in this period, the most cited paper was a survey by Plamondon and Srihari [2] about on-line and off-line handwriting recognition, where the main algorithms that have appeared to date for character and word recognition stages were summarized, as well as the application fields of this technology (e.g., writer authentication, WS or SV, among others).

4.4.6. Period 4: 2005–2009

The fourth period was characterized by four TNs: *Feature Extraction, HMM, Chinese Character Recognition*, and *Writer Identification*. Fig. 14 and Table 6 summarize the most relevant research themes from each of these networks.

As it is shown in the *Feature Extraction* TN, SVM was one of the most importat methodologies to solve document analysis problems. In this period, the use of a specific model of SVM, called Least Squares SVM (LS-SVM), targeted to handwriting recognition problem, was presented by Adankon and Cheriet [75], who demonstrated that this model improved the generalization performance with respect to other previous proposals. This network includes Indian text recognition for the first time. The most important article focusing on this alphabet was due to Bhattacharya and Chaudhuri [56], who proposed the combination of multiresolution representations and MLPs for the recognition of unconstrained handwritten numerals of Indian scripts. In their solution, input numerals pass through three MLP classifiers corresponding to three coarse-to-fine resolution levels in a cascaded composition. These authors also provided a large database for experimentation. Chinese and Arabic scripts were also very important. One of the most influential surveys for Arabic script was published by Lorigo et al. [26]. Jointly with SVM, PCA and NN were some of the most studied methodologies related to those problems. *HMM*s were again a TN, but their importance decreased. Other methodologies related to HMMs were statistical models, ensemble classification, models based on graphs, and recurrent neural networks (RNNs). RNNs often replaced HMMs in word and sentence recognition. Indeed, the most influential paper in this period (with nearly 1000 cites) corresponds to the topic "unconstrained handwriting recognition," and it was written by Graves et al. [4]. While previous systems for this task relied on HMMs with their known limitations, [4] proposed a new type of RNNs, that include long-range bidirectional dependencies, which were suitable for text sequence labeling in situations where data were difficult to segment. Both *Feature Extraction* and *HMM* were motor TNs (although *HMM* was also close to isolated and traversal topics). *Chinese Character Recognition* appeared as a traversal TN that included Elastic Mesh, GA, Fuzzy Logic and Wavelet transform as some of the main related methodologies. *Writer Identification* was an isolated and very studied TN, which was tightly related to Script Identification, Signature Verification, and the Segmentation task.

4.4.7. Period 5: 2010–2014

Since 2010, the problems and methodologies studied in document analysis increased considerably as the number of corresponding TNs. Specifically, there were eight TNs in this period: *Character Recognition* and *HMM* as motor networks, *Segmentation* and *Numeral Recognition* as traversal networks, *Script Identification* and *Chinese Character Recognition* as isolated networks, *Signature Verification* as emerging and traversal TN, and *Historical Documents* as an emerging network. Fig. 15 and Table 7 summarize the most relevant research themes in these TNs. *Character Recognition* network

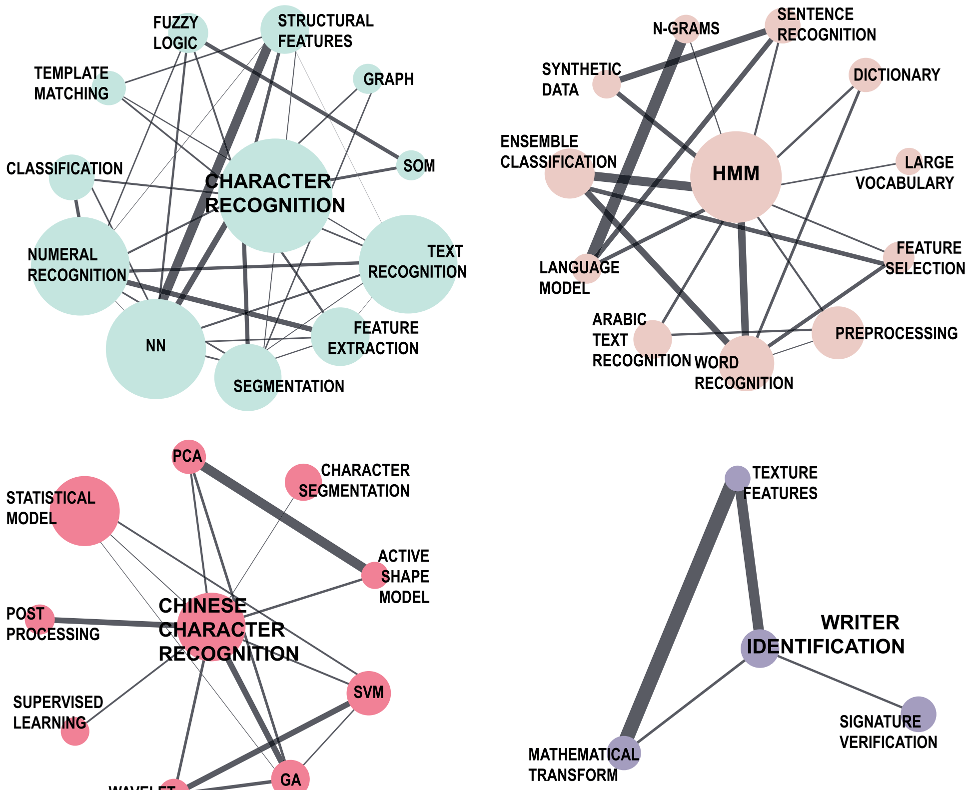

Fig. 13. Thematic networks for Period 3: 2000–2004.

Table 5
TNs' performance for Period 3: 2000–2004.

TN	Network's keywords	#papers	h-index	Top 10 papers
Character Recognition	Character Recognition, Graph, SOM, Text Recognition, Feature Extraction, Segmentation, NN, Numeral Recognition, Classification, Template Matching, Fuzzy Logic, Structural Features	191	38	[2]$_{1749}$ [47]$_{588}$ [50]$_{401}$ [51]$_{314}$ [13]$_{291}$ [55]$_{226}$ [62]$_{177}$ [70]$_{165}$ [79]$_{134}$ [84]$_{130}$
HMM	HMM, Sentence Recognition, Dictionary, Large Vocabulary, Feature Selection, Preprocessing, Word Recognition, Arabic Text Recognition, Language Model, Ensemble Classification, Synthetic Data, N-grams	93	28	[47]$_{588}$ [51]$_{314}$ [13]$_{291}$ [55]$_{226}$ [58]$_{201}$ [74]$_{142}$ [79]$_{134}$ [15]$_{119}$ [16]$_{118}$ [94]$_{118}$
Chinese Character Recognition	Chinese Character Recognition, PCA, Character Segmentation, Active Shape Model, SVM, GA, Wavelet, Supervised Learning, Postprocessing, Statistical Model	88	22	[50]$_{401}$ [70]$_{165}$ [74]$_{142}$ [79]$_{134}$ [99]$_{112}$ [129]$_{83}$ [177]$_{85}$ [178]$_{74}$ [179]$_{66}$ [180]$_{59}$
Writer Identification	Writer Identification, Signature Verification, Mathematical Transform, Texture Features	23	10	[2]$_{1749}$ [53]$_{246}$ [74]$_{142}$ [181]$_{56}$ [182]$_{45}$ [183]$_{29}$ [184]$_{29}$ [185]$_{16}$ [186]$_{15}$ [187]$_{11}$

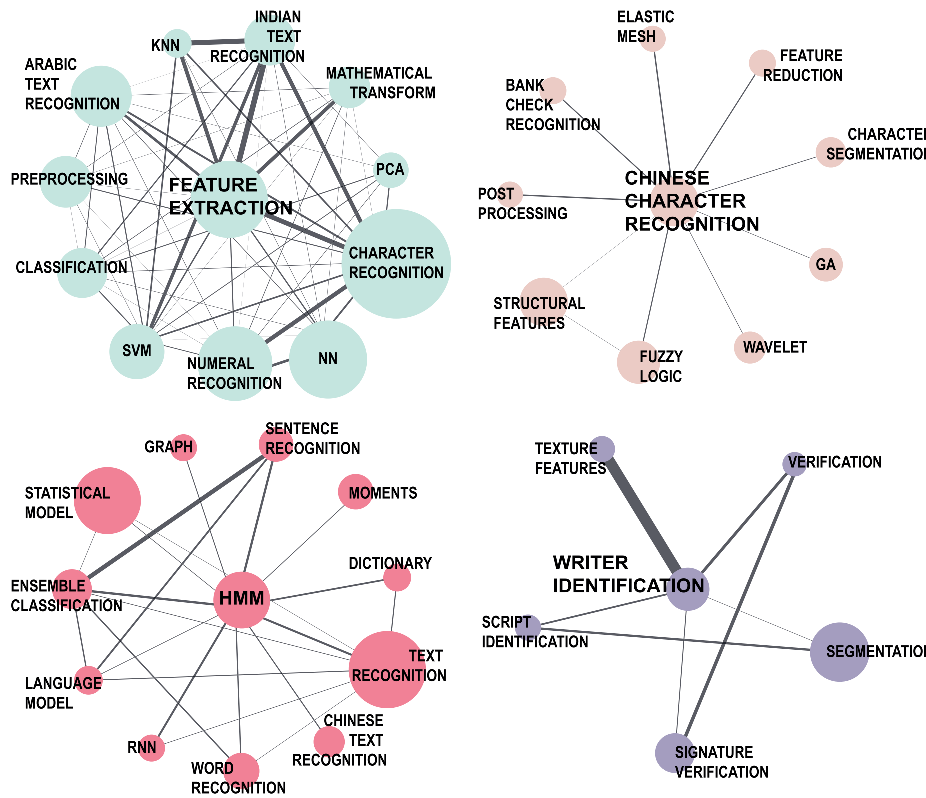

Fig. 14. Thematic networks for Period 4: 2005–2009.

Table 6
TNs' performance for Period 4: 2005–2009.

TN	Network's keywords	#papers	h-index	Top 10 papers
Feature Extraction	Feature Extraction, Indian Text Recognition,Mathematical Transform, PCA, SVM, Character Recognition, NN, Numeral Recognition, Classification, Preprocessing, Arabic Text Recognition, KNN	297	34	[26]$_{342}$ [56]$_{210}$ [59]$_{194}$ [75]$_{140}$ [77]$_{138}$ [78]$_{136}$ [98]$_{113}$ [107]$_{105}$ [115]$_{100}$ [116]$_{100}$
Chinese Character Segmentation	Chinese Character Segmentation, Elastic Mesh, Feature Reduction, Character Segmentation, GA, Wavelet, Fuzzy Logic, Structural Features,Post-processing, Bank Check Recognition	122	19	[59]$_{194}$ [116]$_{100}$ [188]$_{79}$ [189]$_{70}$ [190]$_{65}$ [191]$_{61}$ [192]$_{60}$ [193]$_{52}$ [194]$_{47}$ [195]$_{43}$
HMM	HMM, Sentence Recognition, Moments, Dictionary, Text Recognition, Chinese Text Recognition, Word Recognition, RNN, Language Model, Ensemble Classification, Statistical Model, Graph	198	27	[4]$_{982}$ [21]$_{141}$ [78]$_{136}$ [82]$_{132}$ [98]$_{113}$ [106]$_{106}$ [115]$_{100}$ [116]$_{100}$ [117]$_{100}$ [188]$_{79}$ [196]$_{62}$
Writer Identification	Writer Identification, Signature Verification, Verification, Script Identification, Segmentation, Texture Features	86	17	[115]$_{100}$ [116]$_{100}$ [197]$_{92}$ [198]$_{51}$ [199]$_{43}$ [200]$_{40}$ [201]$_{36}$ [202]$_{34}$ [203]$_{31}$ [204]$_{30}$

was more related to Arabic and Indian text recognition and solved with NN, SVM, KNN, and wavelet approaches (among others). Note that the number of Indian text recognition works grew during this period and, for that, the scope and methodologies of this research became very important to the community.

The *Segmentation* TN is mainly related to text line segmentation, Chinese text and mathematical formula recognition. Those problems were often solved with GA, SOM, and dynamic programming. *HMMs* increased their impact. In addition to the problems addressed in the previous periods, music recognition, WS and Roman text recognition appear now related to this TN. These problems were also often addressed with NN architectures as bayesian networks, RNN and deep belief neural networks (DBNNs), jointly with Gaussian mixture models (GMMs). The *Numeral Recognition* TN was composed of traversal methodologies as PCA, field-programmable gate array (FPGA), and chain codes, and deep learning methodologies as MLP, DNN and autoencoders. *Script Identification* shows that this TN was very related with multi-script problems. *Historical Documents* was related to language models problems. Finally, some highly studied topics and methodologies were Chinese character recognition, independent component analysis (ICA) and CNN, as these keywords appear together in the *Chinese Character Recognition* TN. As the TNs shows, this period was characterized by a high increase in applying deep neural architectures to

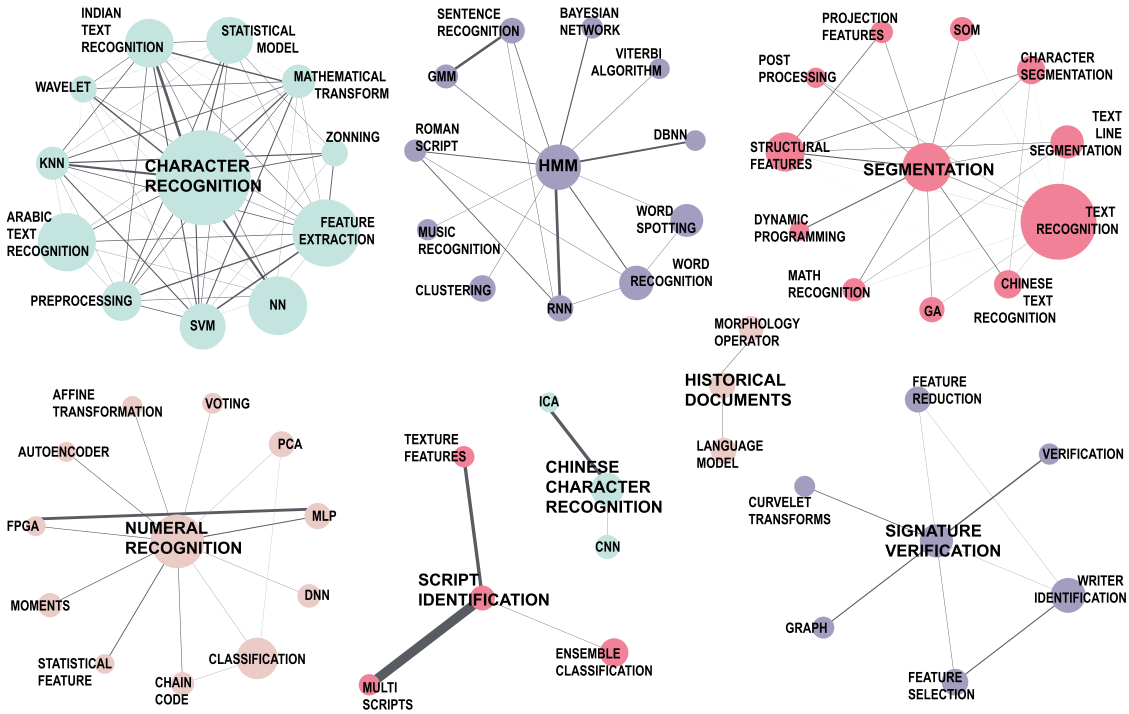

Fig. 15. Thematic networks for Period 5: 2010–2014.

Table 7
TNs' performance for Period 5: 2010–2014.

TN	Network's keywords	#papers	h-index	Top 10 papers
Character Recognition	Character Recognition, Statistical Model, Mathematical Transform, Zonning, Feature Extraction, NN, SVM, Preprocessing, Arabic Text Recognition, KNN, Wavelet, Indian Text Recognition	632	35	[69]$_{168}$ [85]$_{126}$ [97]$_{113}$ [104]$_{106}$ [114]$_{100}$ [205]$_{86}$ [206]$_{85}$ [207]$_{84}$ [208]$_{80}$ [209]$_{79}$
HMM	HMM, Sentence Recognition, Bayesian Network, Viterbi Algorithm, DBNN, Word Spotting, Word Recognition, RNN, Clustering, Music Recognition, Roman Script, GMM	219	29	[54]$_{239}$ [61]$_{186}$ [69]$_{168}$ [104]$_{106}$ [205]$_{86}$ [206]$_{85}$ [210]$_{83}$ [211]$_{82}$ [212]$_{75}$ [213]$_{75}$
Segmentation	Segmentation, SOM, Character Segmentation, Text Line Segmentation, Text Recognition, Chinese Text Recognition, GA, Math Recognition, Dynamic Programming, Structural Features, Postprocessing, Projection Features	386	33	[54]$_{239}$ [61]$_{186}$ [69]$_{168}$ [97]$_{113}$ [104]$_{106}$ [112]$_{101}$ [113]$_{100}$ [114]$_{100}$ [214]$_{86}$ [206]$_{85}$
Numeral Recognition	Numeral Recognition, Voting, PCA, DNN, Classification, Chain Code, Statistical Feature, MLP, Moments, FPGA, Autoencoder, Affine Transformation	231	21	[69]$_{168}$ [207]$_{84}$ [211]$_{82}$ [208]$_{80}$ [215]$_{75}$ [216]$_{54}$ [217]$_{41}$ [218]$_{40}$ [219]$_{38}$ [220]$_{36}$
Script Identification	Script Identification, Ensemble Classification, Multi-scripts, Texture Features	51	14	[221]$_{53}$ [222]$_{30}$ [223]$_{29}$ [224]$_{28}$ [225]$_{23}$ [226]$_{23}$ [227]$_{22}$ [228]$_{22}$ [229]$_{18}$ [230]$_{18}$
Chinese Character Recognition	Chinese Character Recognition, ICA, CNN	57	14	[68]$_{169}$ [209]$_{79}$ [231]$_{46}$ [218]$_{40}$ [232]$_{31}$ [233]$_{25}$ [234]$_{24}$ [235]$_{18}$ [236]$_{18}$ [237]$_{18}$
Historical Documents	Historical Documents, Language Model, Morphology Operator	57	12	[112]$_{101}$ [238]$_{44}$ [239]$_{39}$ [240]$_{33}$ [241]$_{24}$ [242]$_{22}$ [243]$_{22}$ [244]$_{21}$ [245]x_{19} [246]$_{14}$
Signature Verification	Signature Verification, Writer Identification, Feature Selection, Graph, Curvelet Transform, Feature Reduction, Verification	131	18	[214]$_{86}$ [247]$_{80}$ [215]$_{75}$ [248]$_{56}$ [221]$_{53}$ [249]$_{49}$ [250]$_{48}$ [240]$_{33}$ [251]$_{24}$ [252]$_{23}$

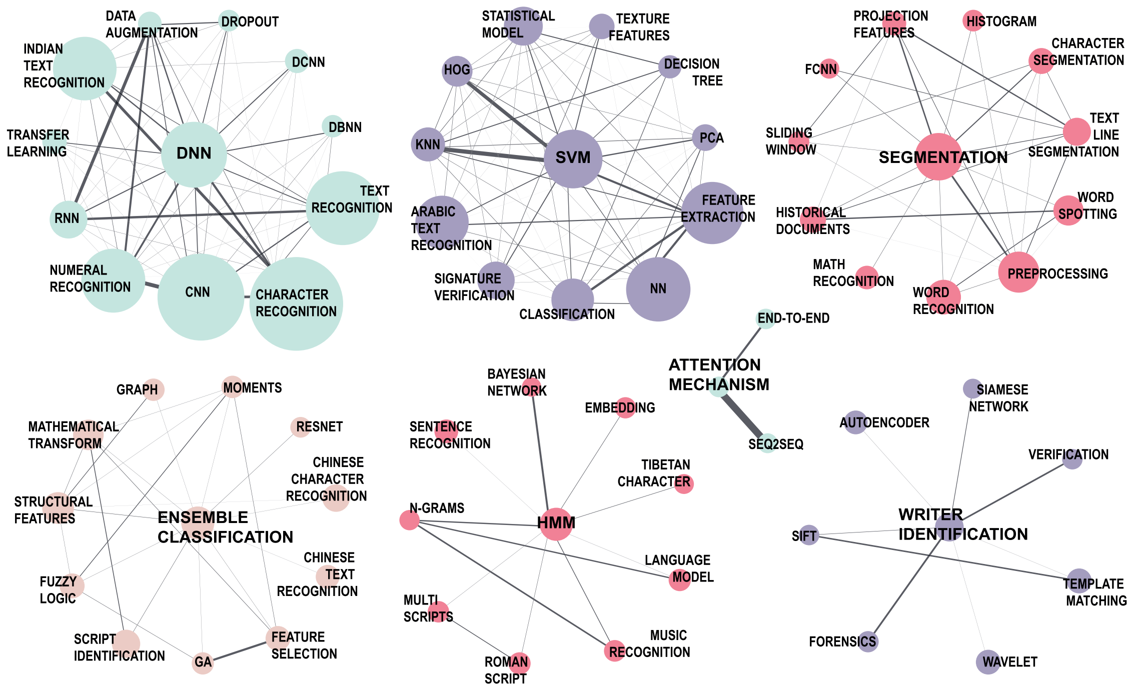

Fig. 16. Thematic networks for Period 6: 2015–2020.

Table 8
TNs' performance for Period 6: 2015–2020.

TN	Network's keywords	#papers	h-index	Top 10 papers
DNN	DNN, Text Recognition, Character Recognition, CNN, Numeral Recognition, RNN, Transfer Learning, Indian Text Recognition, Data Augmentation, Dropout, DCNN, DBNN	1158	30	[71]$_{158}$ [81]$_{132}$ [105]$_{106}$ [120]$_{98}$ [253]$_{82}$ [254]$_{70}$ [255]$_{68}$ [256]$_{68}$ [257]$_{66}$ [258]$_{65}$
SVM	SVM, Texture Features, Decision Tree, PCA, Feature Extraction, NN, Classification, Signature Verification, Arabic Text Recognition, KNN, HOG, Statistical Model, Texture Features	906	23	[95]$_{117}$ [120]$_{98}$ [253]$_{82}$ [259]$_{73}$ [257]$_{66}$ [260]$_{58}$ [261]$_{58}$ [262]$_{54}$ [263]$_{53}$ [264]$_{51}$
Segmentation	Segmentation, Histogram, Character Segmentation, Text Line Segmentation, Word Spotting, Preprocessing, Word Recognition, Math Recognition, Historical Documents, Sliding Window, FCNN, Projection Features	455	18	[95]$_{117}$ [105]$_{106}$ [265]$_{52}$ [266]$_{46}$ [267]$_{45}$ [268]$_{35}$ [144]$_{34}$ [269]$_{27}$ [270]$_{26}$ [271]$_{25}$
Ensemble Classification	Ensemble Classification, Moments, ResNet, Chinese Character Recognition, Chinese Text Recognition, Feature Selection, GA, Script Identification, Fuzzy Logic, Structural Features, Mathematical Transform, Graph	379	20	[71]$_{158}$ [81]$_{132}$ [259]$_{73}$ [255]$_{68}$ [257]$_{66}$ [143]$_{44}$ [272]$_{42}$ [273]$_{35}$ [138]$_{34}$ [274]$_{33}$
HMM	HMM, Embedding,Tibetan Text Recognition, Language Model, Music Recognition, Roman Text Recognition, Multi-Script Recognition, N-Grams, Sentence Recognition, Bayesian Network	165	14	[257]$_{66}$ [265]$_{52}$ [275]$_{52}$ [267]$_{45}$ [269]$_{27}$ [276]$_{25}$ [277]$_{20}$ [278]$_{19}$ [279]$_{18}$ [280]$_{18}$
Attention Mechanism	Attention Mechanism, End-to-end, Seq2Seq	20	7	[266]$_{46}$ [146]$_{31}$ [281]$_{22}$ [282]$_{14}$ [283]$_{12}$ [284]$_{9}$ [285]$_{7}$ [286]$_{6}$ [287]$_{5}$ [288]$_{3}$
Writer Identification	Writer Identification, Siamese Network, Verification, Template Matching, Wavelet, Forensics, SIFT, Autoencoder	155	12	[261]$_{58}$ [275]$_{52}$ [289]$_{29}$ [290]$_{29}$ [28]$_{23}$ [281]$_{22}$ [141]$_{17}$ [291]$_{16}$ [292]$_{15}$ [293]$_{14}$

HTR. In this context, the most cited work was published by Pham et al. [54], who used dropout in recurrent networks (RNNs) with Long Short-Term Memory (LSTM) cells in unconstrained handwriting recognition. This dropout is carefully introduced in the network so that the power of RNN in modeling sequences is preserved. Other relevant works in this period continued using HMMs, as a well-established modeling and recognition paradigm for automatic off-line handwriting recognition, and the IAM database, as the major benchmark for the experiments. The work by España-Boquera et al. [69] proposed a hybrid HMM/Artificial Neural Network (ANN) model, where the structural part of the off-line text image was modeled with an HMM and an MLP-ANN is used to estimate the emission probabilities. This solution was applied to off-line handwritten text lines from the IAM database. Fischer et al. [61] developed a WS system (without pre-segmenting text lines into words) also based on (character) HMM and using the off-line IAM dataset for experiments.

4.4.8. Period 6: 2015–2020

This last period has been characterized by the increasing number of problems and methodologies in the area. Especially, deep learning approaches were widely applied to most of the problems related to document analysis. There were seven TNs: *DNN*, *SVM*, and *Segmentation* as motor TN, *Ensemble Classification* as traversal one, *HMM* and *Writer Identification* as declining TNs, and *Attention Mechanism* as very studied one. Fig. 16 and Table 8 summarize the main research themes for these networks. *DNN* was the main motor TN and was related to text recognition. Specifically, it included deep learning architectures as RNN, DBNN, and Deep Convolutional Neural Networks (DCNNs). The *SVM* TN shows that some of the most used methodologies in SV and Arabic text recognition were SVM PCA, KNN, and HOG.

Segmentation was related to most of the problems of the previous periods, but also to the WS problem, sliding window, and Fully Connected Neural Networks (FCNNs). In this case, sliding windows and FCNNs were often used in holistic or segmentation-free approaches. The network *HMM* shows that Tibetan text, Roman text, multi-script, and music recognition problems, as well as language model, were often solved with Bayesian networks and n-grams methodologies. The *Writer Identification* TN shows that WI, forensic applications, and verification problems, as well as wavelets, template matching, autoencoders, and siamese NN methodologies were declining topics. Finally, *Attention Mechanism* has been a highly developed TN, which relates attention mechanisms, as seq2seq, with end-to-end systems. The vast majority of models proposed for HTR problems were based on several types of DNNs, especially different types of CNNs. Zhong et al. [71] successfully applied GoogleNet to the handwritten Chinese character recognition problem. The work by Hafemann et al. [120] on writer-independent off-line handwritten signature verification (in the presence of skilled forgeries) uses CNNs to address the difficulty of obtaining good features to distinguish genuine signatures from forgeries regardless of the writer. Finally, it is worth mentioning the work by Sudholt and Fink [105] on WS in handwritten documents using a Pyramidal Histogram of Characters (PHOC) CNN-type architecture. This PHOC representation was able to outperform state-of-the-art results for different WS datasets.

5. Conclusions and future research

The following points summarize the **main conclusions** that can be drawn from our analysis:

- For the last thirty years, the literature on off-line handwritten document analysis has grown steadily.
- Japanese, Chinese, Arabic, and Roman scripts were the most studied ones in the first years. Publications on Indian scripts have grown notably for the last years.
- Character and numeral recognition have been the most studied text recognition problems. Since 1995 and 2000, word and sentence recognition, respectively, have also attracted attention.
- WS, WI, SV, and historical text recognition have been investigated recurrently.
- Other less studied topics related to text recognition are music recognition, mathematical formula recognition, forensic applications, and other verification problems.
- Text segmentation and classification have been crucial to tackle text recognition. In particular, the combination of several classification models to solve the issues has stood out. Besides, researchers have dealt with the feature extraction task considerably, as many keywords in the TNs show.
- HMMs, SVMs, and NNs have been motor methodologies over the years. Within the NNs, the DNNs and their variants such as RNNs, DCNNs, FCNNs have set the trend in research for the last six years. Nevertheless, the methodologies used have been many and varied.

Also, as mentioned in Section 3.3.2, looking at the last periods' motor TNs and the most recent published works, some **short-term future trends** can be figured out:

- Text recognition problems seem to lead the document analysis research. Within this field, HCR has been in a motor TN for last thirty years.
- Since 2000, *Segmentation* has become increasingly important as an integral step in HTR, and in the short-term future, it will probably keep being a relevant topic. Moreover, other topics included in this TN, such as HWR, WS, Historical documents recognition, and techniques as FCNN and sliding window, will probably be relevant in the next years.
- SVM and its related topics became traversal topics, but in the last fifteen years it has exhibited high centrality and density, increasing its importance on the research field. Also, its number of papers has increased.
- DNNs appeared strongly in 2015–2020, showing the highest density, centrality, and number of papers of all topics. So, it is expected that deep learning keeps being an essential research theme in the short term.
- The importance of a problem or a technique in a specific period depends on the script to be recognized. For example, HCR has been deeper studied in Chinese, Arabic, or Roman (or Latin) scripts since 1990, and in the 2000s word recognition problems were more important. However, handwriting recognition for Indian scripts started later (over 2005), and HCR problems became very important between 2010 and 2014. In the same way, a methodology that was very important in a period and could seem out of use could be fundamental in future periods as other scripts could use it to solve the problem.
- Many recent articles are focused on an end-to-end approach that includes localization plus transcription. Other handwriting text recognition models are based on sequence-to-sequence and attention mechanisms, as it is shown in the *Attention Mechanism* TN. In this last approach, classical attention mechanisms are replaced by transformers. Additionally, multi-script systems have become very popular, especially in Indian text recognition, where many alphabets coexist.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal financial interests or personal relationships

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