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Article

Structure and evolution of sensor research to forecast emerging scientific and technological directions

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Abstract: How do sensor research and technologies grow over time? This paper applies the network analysis with a new computational approach to map the structure and evolution of sensor research and technologies over a 30-year time frame (1990-2020).The goal of this study is to analyze the evolution of sensor research for forecasting emerging scientific and technological trajectories. Results show that the scientific interaction within ecosystem (represented with networks) of sensor generates a co-evolution of scientific fields supporting the accelerated growth of different technological trajectories, such as: wireless sensors, fiber optic and optical sensors, gas sensors and biosensors. These results suggest main theoretical implications that explain the evolution of sensor research with critical aspects of innovation management to support R&D investments towards new technological trajectories having a high potential of growth.

Keywords: Sensor research; Sensor technology; Network analysis; Technological trajectories; Technological change; Scientific change; Scientific development; Wireless sensor networks; Fiber optic sensors; Biosensors.

1. Introduction

The research field of sensor is undergoing a significant change to support the evolution of science and technologies in society [1-2]. The goal of this study is to analyze the scientific ecosystem (interacting research fields) of sensor research and technologies over time to show interactions supporting technological trajectories directed to fulfil human goals and needs, and solve problems in society. In particular, this paper investigates sensor research and technologies, from 1990 to 2020 period, to clarify major changes in the scientific structure over these 30 years [3-6]. In general, technological change in sensor research can support new technologies, such as smart or intelligent sensors [7-10] and the Internet of Things [11-13]. New sensors are sustaining a critical technological and social change [14]. In a context of computational scientometrics, this study here endeavors to explain the evolution of sensor research and sensor technologies with maps or networks showing the interactions between scientific publications that are a main unit of analysis to understand the organization and evolution of science in this field [15-17]. The crux of this study is rooted in scientometrics (the study of quantitative characteristics of science and scientific research) and since this approach is un-common in this journal on the science and technology of sensors, some brief backgrounds is useful to understand and clarify it.

Leydesdorff (2007) has developed studies by generating a map of the whole set of journals, showing centrality measures to clarify citation environments (small sets of journals where citing is above a certain threshold)[18]. Instead, Klavans and Boyack (2006) identify a new measure of relatedness between bibliometric units (e.g., journals, words, etc.) for mapping science and providing critical aspects for structure and evolution of science [19]. Relatedness measures have also a vital role in showing the relationship between data items (cf., [20]). Small (1999) argues that the network of linkages from document to document and from discipline to discipline can show crossover fields and offer the possibility of exploring extended knowledge pathways and new technological trajectories [21]. Boyack et al. (2005) maintain that science maps provide main aspects to visually identify major research fields of science and emerging technologies, their size and interconnectedness [22]. Scholars also argue that emerging general purpose technologies and new discoveries induce radical novelty, accelerated growth, and main socioeconomic impacts [23-27]. Manifold techniques have been developed in scientometrics and social study of innovation to detect and analyze the emergence of research fields and technology domains [16, 28-35]. These methods are based on large datasets and computational approaches that allow the computing of complex indicators for detecting new technological trajectories and patterns in science [36]. Quantitative approaches, based on bibliometric data of publications, are useful techniques to capture information earlier in the cycle of technology development, whereas patents, in contrast, trail behind [37]. In this research stream, this study here has the purpose of mapping the ecosystem of sensor research and technologies with networks (in this case ecosystem is a community of research fields and technologies that interact, forming a complex network of interconnected elements that evolve over time) to analyze structure and evolution over a 30-year time frame. This scientometric analysis can show interaction between research fields and technologies that sustain the evolution of sensors in science, technology and society. The explanation of relationships in the section of discussion clarifies some characteristics of the structure and evolution of sensor networks with interesting theoretical and managerial implications for the scientific and technological development of sensors.

2. Materials and Methods

2.1 Data-processing resources

In this study, we use the Web of Science (WOS) Core collection database 2022 to retrieve sensor research and technologies literature documentations [38].

Web of Science is a main source of data for bibliometric analysis of sensor research [38]. There are three subfield databases in Web of Science: the Science Citation Index (SCI), the Social Sciences Citation Index (SSCI) and the Arts and Humanities Citation Index (AHCI). Approximately more than 10,000 journals from a total of about a million that circulate worldwide are included in the database; Web of Science a database that contains mainstream journals [39]. Web of Science is used here because it offers a lot of information, a variety of metadata, including abstracts, authors, institutions, citations, references, and the journal impact factor, which are crucial aspects for accurate bibliometric analysis (cf., [40-42]).

The term "sensor" was searched in Web of Science (2022) in the section of topics of articles [38]. The results are refined by documents type = (Articles), Language = (English), Timespan = 1990-2020, and Indexes = (SCI-EXPANDED).

The sample contains 362,362 papers split into three distinguished timespans, given by 1990-2000, 2001-2010, and 2011-2020.

2.2. Data processing procedure and computational approach for network analysis

To address the main purpose of this study, we use articles original keywords (DEs) as the basis for building the keywords co-occurrence in networks regarding sensor research and technologies. We also implement this approach to visualize the interconnection between sensor research fields and technologies to analyze and interpret the evolving relationship between technologies in sensor networks. We also use the co-occurrence measurement to study the interconnection between different sensor sub-technologies [43]. The methodology of co-occurrences is commonly used for identifying the underlying collaborative structure between terms. Two terms (keywords, journals, research disciplines, countries, authors, etc.) are considered co-occurred whenever they simultaneously appear in a single document [44]. Scholars have widely used this approach to analyze the interconnection between different research fields (e.g., [45]). In this study, we use the "Original Keywords" as the basis for representing the sensor research and technologies and creating the interconnection network between words. These words are known by the DE tag in the Web of Science bibliometric data, and they are separated by semicolon. In particular, to construct the co-occurrence networks between words, we apply the following data processing-procedures:

- Bibliographic data were downloaded from the Web of Science (2022) database [38] and split into three periods: 1990 to 2000, 2001 to 2010, and 2011 to 2020.
- All the combined phrases that lack "sensor", "sensing", and "sense" were removed and then removed the adjective clauses. This step focus only on words related to sensor technologies (for instance, biosensors, wireless sensor networks, gas sensors, etc.).
- We use Python programming language version 3.6.5 and Scikit-learn library version 0.23.2 for constructing the co-occurrence matrix [46]. In this step, we determine a threshold and removed the words with lower than ten times co-occurrences.
- Afterwards, we utilize Gephi software version 0.9.2 to visualize the co-occurrences matrix and calculate the network measures [47]. The node indicates the words related to sensor research and technologies, and a link makes a connection between two words whenever they appear in at least ten articles. To put it differently, a link means two different words co-occurring on at least ten articles. The color of nodes also represents the community: when two nodes have a similar color, they are in the same community in the classification. The thickness of each edge represents the weight of co-occurrences. If more than two terms appear in the same documents; the connected edge will be thicker.

After creating the word co-occurrences networks for each period, we apply measures to analyze the structure and to explain the evolving patterns of sensor research and technologies over time [48]:

– Degree centrality (DC): defined as the number of edges a node has [49]. In the word co-occurrence networks, degree stands for the total number of words that appear with the node in the same documents. Degree centrality of node v is given by:

$$DC(v) = \sum_{v,g=1}^{n} Edge\ (g)$$

where
DC(v)=Degree centrality of node v
g= edge

– Betweenness centrality (BC): it shows how much a node is essential to create connections with other nodes in the shortest path. Betweenness Centrality of node v is calculated by the following formula [50, 56]:

$$BC(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (1)$$

where:
BC= Betweenness Centrality measure of node v
σ_{st} = Total number of shortest paths from nodes s to node t
$\sigma_{st}\ (v)$ = Number of shortest paths from s to t going through v

– A node's Closeness Centrality (CC) is an indicator of a network centrality: it is the number of links needed to connect each node in the network with all the other nodes in the network or the average number of links required to reach all other nodes in the network from a node in the network [6].

$$CC(v) = \frac{1}{\sum_{u \in V} d(v,u)}$$

where:
CC = Closeness Centrality measure of node v
d(v, u) is a shortest path between nodes v and u.
$\sum$ is the sum of the path lengths from node v to all other nodes in the network

– Finally, Community structure represents the categorization of technologies interconnection using the modularity algorithm to distinguish the classifications [51]. The number of communities calculated by modularity function (Q):

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \qquad (2)$$

where:
Q = modularity function
A_{ij} = weight of the connection from i to j
k_i *degree of vertex* $i = \sum_j A_{ij}$ = sum of the weights of the edge attached to vertex i
k_j *degree of vertex* $j = \sum_i A_{ij}$ = sum of the weights of the edge attached to vertex j
c_i = Community to which vertex i is assigned
c_j = Community to which vertex j is assigned
$m = ½ \sum ij \ A_{ij}$ = number of edges in the graph
$\delta -$ function $\delta(c_i, c_j)$ is 1 if $c_i = c_j$ and 0 otherwise.

Co-occurrences networks generated by Gephi save in GraphMl format and imported into SCI2 software version 1.3 to implement the community detection algorithm.

We use Degree Centrality (DC) to analyze the evolution of nodes over time and utilize community structuring to detect the classified technologies that have the highest interconnections to track the transition of linkages between sensor research and technologies. We use also Betweenness Centrality (BC) measures to indicate the nodes' role in facilitating the connection of sub-technologies at the heart of three understudying networks. Nodes with the highest score of BC, they have a position to be a bridge for connections among the other network nodes [52].

3. Results and Discussions

3.1. The ecosystem of sensor research and technologies in 1990-2000 period

The ecosystem of sensor research and technologies in the 1990-2000 period shows a network concerning the words regarding sensor research fields and technologies (Figure 1A). The total number of articles in this time frame dataset is 30,674 records. Figure 1A also shows the network of co-occurrences of these terms from 1990 to 2000. This network of Figure 1A (1990-2000) includes 72 nodes and 194 edges and 5 communities. Table 1 shows that "biosensor", "gas sensor", and "optical sensor" have the highest degree centrality compared to other nodes: these three technologies have a higher interaction with other technologies at the highest level. Results of Table 1 also suggest a high centrality degree for "fiber optic sensor" and "pressure sensor" among all nodes in the network. We have in Figure 1A four communities, in which "biosensor"–with a centrality degree score of 23–has a strong relationship with "oxygen sensor", "ph. sensor", "immune sensor" and "capacitive sensor". Based on edge weight, these technologies have a high level of co-occurrence in documents leading to an interconnected community. Moreover, "gas sensor" with a centrality degree score of 21 is in the head of the community number 4, strongly connected to other sub-technologies, including "humidity sensor", "potentiometric sensor", and "amperometric sensor". In the second community, the "optical sensor"–with a centrality degree score of 20– is highly connected to the "fiber optic sensor", "temperature sensor", and "displacement sensor". The remaining technologies are classified in a community called number 1, which has the highest number of nodes. In the community, the "pressure sensor" with a degree number of 18 is highly interconnected with "chemical sensor", "micro sensor", "smart sensor", "thermal sensor", and "integrated sensor".

3.2. The ecosystem of sensor research and technologies in 2001-2010 period.

This period shows an ecosystem based on a network of interaction with a growing number of nodes (197) and edges (623). This time frame contains 83,512 records, 23 percent of total articles. This period has 9 communities. Figure 1B shows that the leading technologies in the ecosystem of 2001-2010 period are "biosensor", "chemical sensor", "gas sensor", and "optical sensor". The most interconnected technologies considering the edge weight are "active pixel sensor" and "cmos image sensor", "biosensor" and "immunosensor", "strain sensor" with "temperature sensor" and "biosensor" and "chemical sensor". Table 1 shows that the top five sensor technologies on 2001-2010 period are "biosensor" with centrality degree of 53, included in community number 2 that is highly connected to "electrochemical sensor"; "chemical sensor" with centrality degree of 48 is included in the fourth community with "gas sensor" having centrality degree of 46 and "humidity sensor". "Optical sensor" with centrality degree 46 is highly connected with "oxygen sensor" and "glucose sensor" as community number 6. This result confirms the growing role of Optical sensors as forecasted by Andersen et al. [1]. Moreover, "fiber optic sensor" with centrality degree of 40 has the highest interconnection with "temperature sensor", "magnetic sensor", and "strain sensor" and is included in the fifth community. These nodes with the highest level of centrality degree score among all the nodes represent a high diversified interconnection with other sensor technologies compared to other nodes in this network. Interestingly, unlike previous period, the "fiber optic sensor" is separated as a new interconnected network from the "optical sensor" community. Our results show that during the second decade, the "wireless sensor network", "wireless sensor", and "remote sensor" co-occurrences in documents gained momentum with other technologies and emerged in the top 20 topics with the highest level of degree centrality.

3.3. The ecosystem of sensor research and technologies in 2011-2020 period

Finally, the scientific ecosystem based on interconnection between sensor technologies in 2011-2020 contains 249,492 records, 69 percent of all articles collected in this study (see Figure 1C). The co-occurrence network of sensor technologies comprises 553 nodes and 2696 edges. "Strain sensor" with "temperature sensor", "compressed sensing" with "wireless sensor network", "biosensor" with "immunosensor", "rechargeable sensor networks" with "wireless sensor network", and "colorimetric chemosensor" with "fluorescent chemosensor" have strong relationships based on their edge weight score and are classified in 8 communities (cf., [53-55]). Figure 1C shows that the size of nodes and network linkage have been growing and creating an ecosystem based on complex interconnection communities between manifold sensor research fields and technologies. The leading technologies in this period are "optical sensor" with a centrality degree of 128, "biosensor" with a centrality degree score of 126, "wireless sensor network" with a centrality degree score of 121, "fiber optic sensor" with a centrality degree of 120, "temperature sensor" with a centrality degree of 111. Table 1 shows the top 20 technologies considering centrality degree values: the top five sensor technologies are "optical sensor" with a centrality degree score of 128 included in community number 6 that has a high interaction with "fluorescent sensor"; "biosensor" with a centrality degree of 126 is strongly associated with "chemical sensor" and "electrochemical sensor ". Surprisingly, these two technologies with the highest centrality degree in the previous decade has their separated interconnection in two different communities with other technologies. In this decade, although the "chemical sensor" rank, based on the degree of centrality decreased, it started a process of merging with "biosensor" in the same community. The growing role of biosensor in ecosystem confirms the preliminary study by Andersen et al. (2004) when the evolution and potential aspects of this sensor are rather ambiguous [1]. The "wireless sensor network" with a centrality degree of 121 expands its interconnection community and gets the third rank in a degree centrality scoring. Moreover, sensor technologies in community number 3 are not present in the top 20 topics; this vital finding suggests that although the "wireless sensor" technology increases its interconnection and diversification with other related technologies, it is an emerging technology that has not generated strong relationships with other top technologies. This evolutionary characteristic also is present for "fiber optic sensor"; moreover, the "optical sensor" that was the head of the community including "fiber optic sensor" has stopped its growth and is not in the top 20 topics having high degree centrality score. Instead, the "temperature sensor" that was included in the same community with "fiber optic sensor", emerged as a new community in this decade and started expanding its own technology interconnection community.

Table 1. Top 20 sensor technologies in networks with the highest centrality degree over 1990-2020 period

1990-2000			2001-2010			2011-2020		
Word	Degree Centrality	Community	Word	Degree Centrality	Community	Word	Degree Centrality	Community
biosensor	**23**	**3**	biosensor	53	2	optical sensor	128	6
gas sensor	21	4	chemical sensor	48	4	biosensor	126	2
optical sensor	20	2	gas sensor	46	4	wireless sensor network	121	3
fiber optic sensor	20	2	optical sensor	46	6	fiber optic sensor	120	5
pressure sensor	18	1	fiber optic sensor	40	5	temperature sensor	111	1
chemical sensor	16	1	wireless sensor network	31	1	gas sensor	109	4
micro sensor	12	1	capacitive sensor	31	3	chemical sensor	83	2
oxygen sensor	12	3	temperature sensor	29	5	capacitive sensor	77	1
humidity sensor	11	4	micro sensor	28	3	pressure sensor	72	1
ph. sensor	11	3	electrochemical sensor	27	2	strain sensor	72	1
smart sensor	11	1	pressure sensor	25	3	humidity sensor	72	4
thermal sensor	11	1	ph. sensor	24	7	electrochemical sensor	71	2
flow sensor	10	1	oxygen sensor	22	6	wearable sensor	70	1
temperature sensor	10	2	wireless sensor	20	1	wireless sensor	59	1
integrated sensor	9	1	magnetic sensor	19	5	ph sensor	59	2
immunosensor	9	3	remote sensor	19	1	flexible sensor	55	1
capacitive sensor	8	3	strain sensor	18	5	magnetic sensor	53	1
potentiometric sensor	8	4	glucose sensor	17	6	fluorescent sensor	52	6
amperometric sensor	8	4	humidity sensor	17	4	remote sensor	52	7
displacement sensor	7	2	amperometric sensor	17	3	nano sensor	49	4

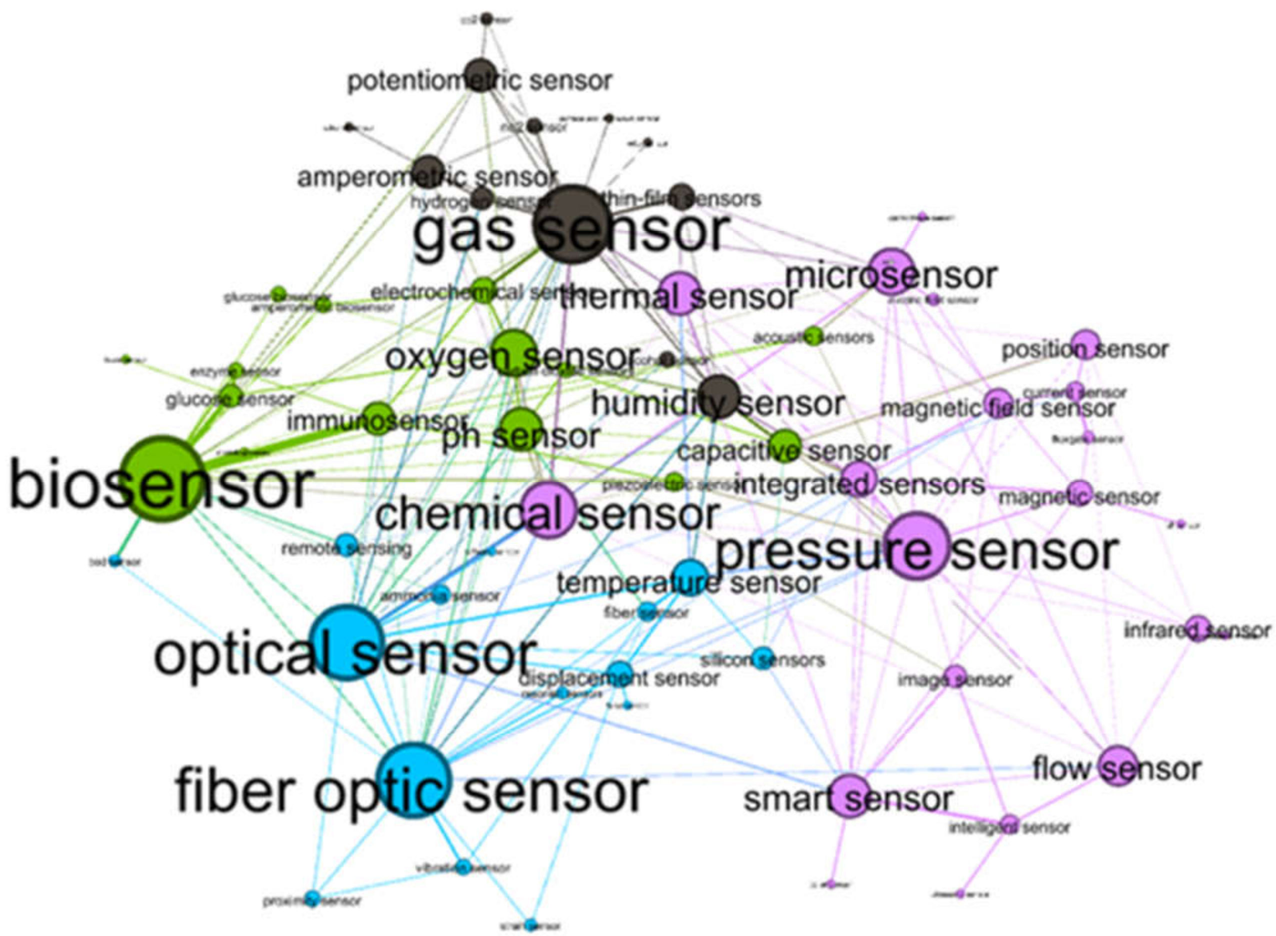

Figure 1A. Structure and evolution of scientific and technological networks in sensor from 1990 to 2000

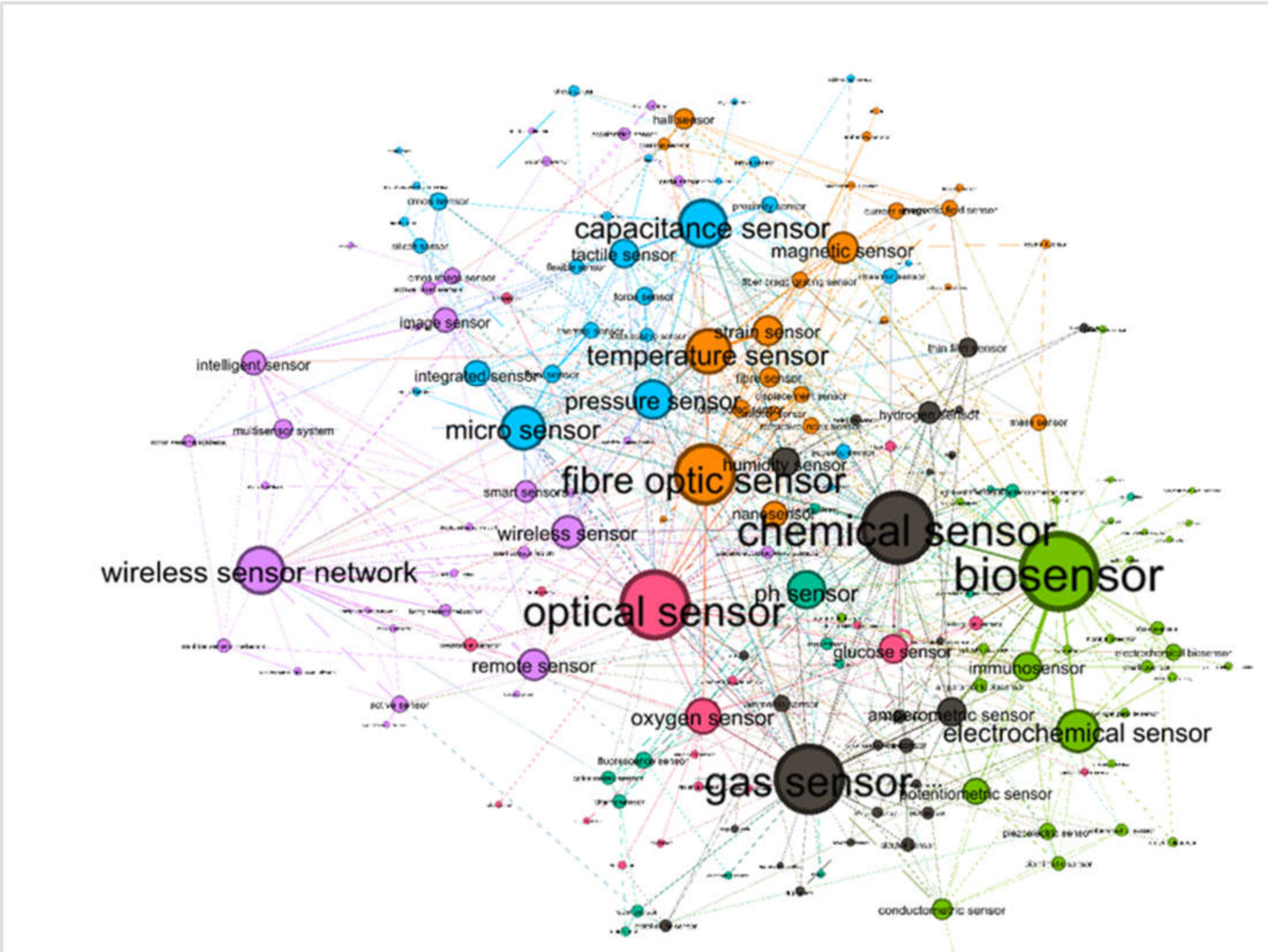

Figure 1B. Structure and evolution of scientific and technological networks in sensor from 2001-2010

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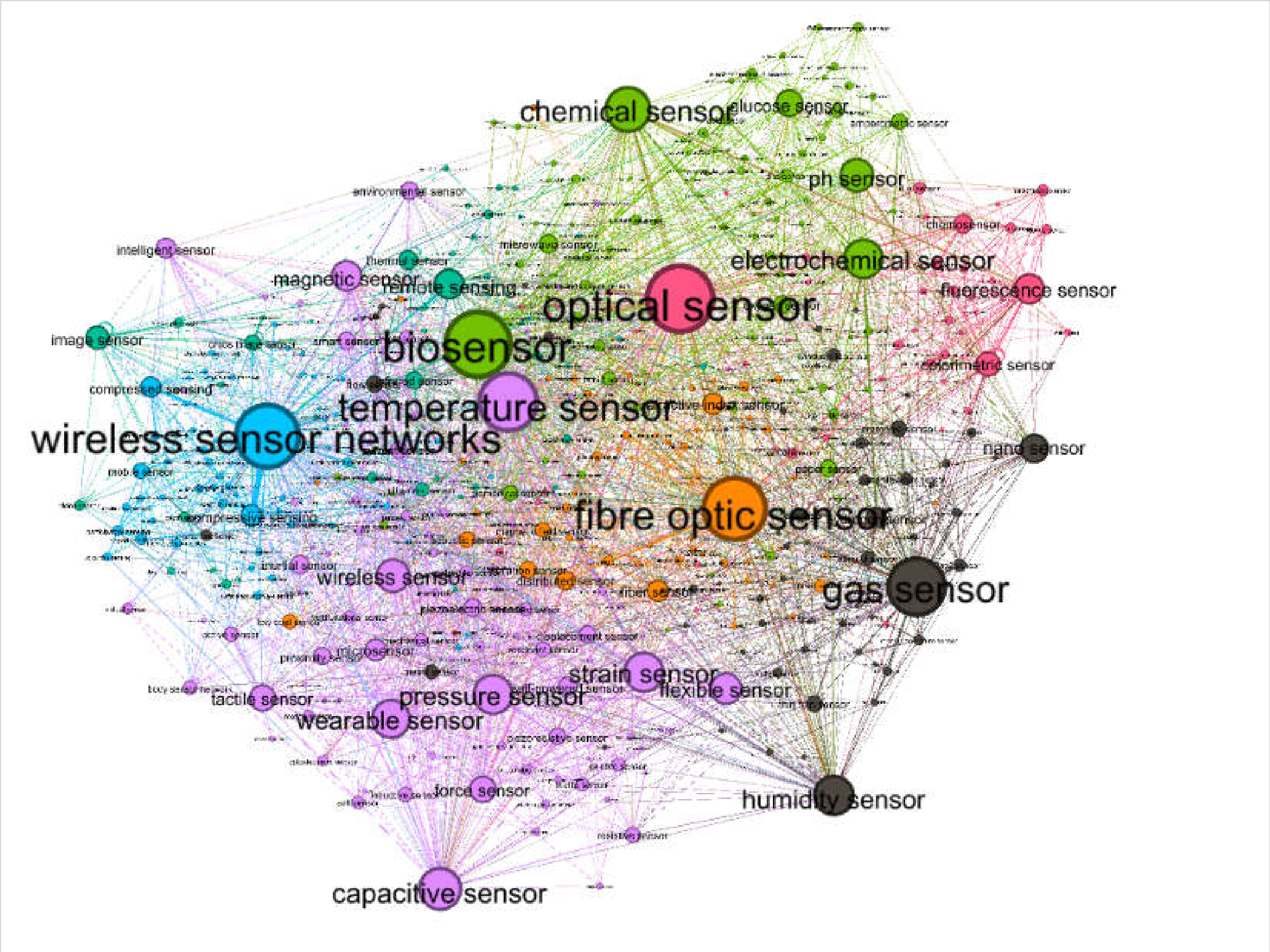

Figure 1C. Structure and evolution of scientific and technological networks in sensor from 2011-2020

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3.4. General discussion of the evolution of ecosystem in sensor technologies, 1990—2020 period

The evolution of ecosystem in sensor technologies is represented with a change of network indicators. In particular, network's average degree increases from 5.4 to 10.6 over 1990 – 2020 period and suggests growing technological interconnections. However, the density of interconnection structures has been decreasing from the first decade: the closeness of centrality degree of network and the interconnection between sensor technologies based on their co-occurrence have deteriorated. Moreover, the decreasing magnitude of betweenness centrality demonstrates that there is a lower dependency on some nodes having a bridging role, such that a lot of sensor technologies have connections directly with other technologies instead of making connections through intermediate technologies. The increasing level of closeness centrality and the stable number of communities suggest that the independence level of degrees connecting other nodes has been elevating (cf., [56]): technological interconnection in sensors tends to be more centralized, and the differences between communities or degrees tend to gradually increase. Results also show that the top ten sensor technologies have a technological evolution from three perspectives: direct connection, interconnection, and diversified interconnection. The centrality degree of a single node in a network indicates the potential aspect that could facilitate the interaction within the network [43]. In addition, results show that optical sensor, biosensor, fiber optic sensor and wireless sensor are central technologies directly linked to other nodes in the network [55, 57-60]. The wearable sensor, which has emerged later than other technologies, tends to have a high potential growth and interaction with other sensor technologies because of rapid improvement of degree of centrality. Finally, in ecosystem of sensors, based on interconnection networks, technologies tend to have a greater capacity to interact with other technologies (cf., [61]; and theory of technological parasitism by [62-64].

The technologies with a higher closeness centrality score have a low distance from their community nodes and a high distance from other excluded nodes. The technologies with a high level of closeness centrality (CC), including "optical sensor", "biosensor", "fiber optic sensor", "gas sensor", and "wireless sensor networks", have a powerful evolution and create distinct communities. Aside from DC level and CC score, the top ten technologies with higher betweenness centrality have a higher diversification than technologies with the highest level of closeness centrality.

The evolution of interconnection between sensor technologies in the top 20 sensors from 1990 to 2020 is in table 2. Sensors with the highest centrality degree scores in 1990-2000 (biosensor, gas sensor, optical sensor, fiber optical sensor, pressure sensor, and chemical sensor) have been expanding over time. Some technologies, such as "strain sensor" had a low centrality degree score in the first period but it has increased to centrality degree of 18 and ranked 17 in the second period, reaching consequently a centrality degree score of 70 and rank 10 in the last period (2011-2020). Moreover, the "temperature sensor" rank improved from 15 with an initial degree of 9 (first period) to rank 8 and a degree score of 29 in the second period and finally rank 5 with a degree score of 118 in the last period under study. The "capacitive sensor" ranked 18 with an initial degree score of 8, elevated ultimately to 8 in the last period, whereas "electrochemical sensor" with a degree of 6 and rank 23 has improved to rank 13 with a degree score of 69 in the last period.

These results show that technologies' positions have evolutionary phases of transition in the network and converge towards vital nodes with the highest number of interconnections over time [6, 63, 65-66].

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Table 2. Top 20 sensor technology and research fields with measures of the evolution of networks from 1990 to 2020

1990-2000					2001-2010					2011-2020				
Label	DC	BC	CC	community	Label	DC	BC	CC	community	Label	DC	BC	CC	community
biosensor	23	0.149	0.563	2	biosensor	53	0.135	0.562	1	optical sensor	128	0.122	0.556	5
gas sensor	21	0.128	0.558	3	chemical sensor	48	0.080	0.555	3	biosensor	126	0.137	0.553	1
optical sensor	20	0.131	0.563	1	gas sensor	46	0.090	0.538	3	fibre optic sensor	120	0.126	0.544	4
fiber optic sensor	20	0.113	0.553	1	optical sensor	46	0.067	0.553	5	wireless sensor net-works	118	0.146	0.532	2
pressure sensor	18	0.072	0.525	0	fibre optic sensor	40	0.072	0.525	4	temperature sensor	111	0.079	0.543	0
chemical sensor	15	0.042	0.534	0	wireless sensor network*	31	0.056	0.488	0	gas sensor	109	0.095	0.535	3
microsensor	12	0.063	0.488	0	capacitive sensor	31	0.045	0.487	2	chemical sensor	83	0.044	0.515	1
oxygen sensor	12	0.032	0.496	2	temperature sensor	29	0.017	0.491	4	capacitive sensor	75	0.035	0.507	0
humidity sensor	11	0.018	0.473	3	micro sensor	28	0.026	0.517	2	strain sensor	70	0.032	0.506	0
ph sensor	11	0.036	0.484	2	electrochemical sensor	27	0.028	0.482	1	pressure sensor	72	0.030	0.488	0
smart sensor	11	0.052	0.462	0	pressure sensor	25	0.013	0.472	2	humidity sensor	70	0.029	0.496	3
thermal sensor	11	0.014	0.469	0	ph sensor	24	0.021	0.486	6	wearable sensor	70	0.034	0.511	0
flow sensor	10	0.032	0.480	0	oxygen sensor	22	0.030	0.478	5	electrochemical sensor	69	0.049	0.501	1
integrated sensors	9	0.020	0.473	0	wireless sensor*	20	0.013	0.461	0	wireless sensor	59	0.025	0.484	0
temperature sensor	9	0.016	0.449	1	magnetic sensor	19	0.021	0.446	4	ph sensor	59	0.024	0.498	1
amperometric sensor	8	0.008	0.459	3	remote sensor	19	0.020	0.475	0	flexible sensor	55	0.020	0.471	0
capacitive sensor	8	0.013	0.439	2	strain sensor	18	0.014	0.469	4	remote sensor	52	0.038	0.487	6
immunosensor	8	0.010	0.442	2	glucose sensor	17	0.006	0.440	5	magnetic sensor	51	0.018	0.479	0
potentiometric sensor	8	0.012	0.427	3	humidity sensor	17	0.010	0.456	3	fluorescence sensor	50	0.032	0.458	5
position sensor	7	0.005	0.416	0	amperometric sensor	17	0.010	0.434	3	nanosensor	49	0.019	0.474	3

Note: highlight grey cells indicate emerging sensors after 2000. DC=Degree centrality; BC= Betweenness centrality; CC =closeness centrality.

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Table 3 shows emerging technologies: terms that came up in the network after 1990-2000 period and started an evolutionary growth. Finally, the emerging technologies have increased from 137 in 2001-2010 to 374 in the 2011-2020 period. This finding reveals that sensor research and technologies have a significant and continuous evolution in science and society.

Table 3. Top 20 emerging sensor technologies in networks from 2001 to 2020

Top 20 emerging sensor technologies				
	2001-2010		**2011-2020**	
Rank	Label	Degree centrality	Label	Degree centrality
1	wireless sensor network	31	self-powered sensor	30
2	wireless sensor	20	environmental sensor	28
3	nano sensor	15	biomedical sensor	22
4	conductometric sensor	11	inductive sensor	21
5	distributed sensor	9	paper sensor	26
6	cmos sensor	9	low-cost sensor	21
7	cmos image sensor	9	liquid sensor	19
8	electrochemical biosensor	8	printed sensor	19
9	mass sensor	8	textile sensor	19
10	fiber bragg grating sensor	8	body sensor network	20
11	refractive index sensor	8	light sensor	18
12	fluorescence sensor	8	mechanical sensor	19
13	active sensor	8	aptasensor	16
14	light-addressable potentiometric sensor	6	dual sensor	16
15	active pixel sensor	6	ratiometric sensor	14
16	colorimetric sensor	6	biomimetic sensor	15
17	flexible sensor	6	chemiresistive sensor	17
18	wearable sensor	6	multifunctional sensor	17
19	dna sensor	6	visual sensor	13
20	biomimetic sensor	6	copper sensor	13

3.5. Principal theoretical implications evolutionary networks in sensor research and technologies

These results suggest some properties of the scientific change of the ecosystem of sensor research and technologies that can support general principles for the evolution of science and technology (cf., [6, 26, 28, 32, 67]):

Firstly, sensor technologies co-evolve in ecosystem with complex interactions between different technologies. In fact, the level of interconnections between sensor-related technologies is increasing over time dramatically.

Secondly, some sensor technologies achieve a critical position in the ecosystem, playing a connective role of master technology for other technologies. For instance, wireless sensor networks increased exponentially in the ecosystem having a bridging and supporting role compared to other technologies.

Thirdly, sensor technologies are generating new trajectories of technological specialization during their co-evolutionary pathways in the ecosystem.

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The finding of the study here suggests that the evolution of sensor research and technology proceeds with the following evolutionary typologies (Figure 2):

- *Total fusion* of research fields is when two or more research fields (e.g., A and B) merge and create a new one (i.e., AB) that evolves as a whole system. For instance, in sensor research: Nano-Bio Sensor is a fusion of Nanosensor and Biosensor. In particular, the combination of these two technologies and research fields created a new potential field, which is dependent from its initial source fields.
- *Partial fusion* is, during the scientific change, the incorporation of a smaller research field (e.g., B) into a large research field (e.g., A), generating a super research field A' (that embodies B). For instance, in sensor research, the "chemical sensor" is also including parts of materials science (e.g., graphene) with the goal to generate ion/molecule sensors applied in pharmaceutical, and food production.
- *Total splitting (total fission)* is when research field A (including a research field B) splits up in research fields A and B that have autonomous evolutionary trajectories. For instance, in sensor research: Polymer sensor is a technology born in the Chemical sensor community, afterwards it grew up independently and created its own domain of study.
- *Partial splitting (partial fission)* is when research field A (containing research fields B and C) develops by splitting in a research field A'' also containing B and a research field C that splits off from the original set A; both research fields have autonomous evolutionary trajectories. For instance, in sensor research: both gas sensors and liquid sensors dawned in the chemical sensors field; after a while, gas sensors started their evolution independently from chemical sensors and created their own domain; however, liquid sensors cannot still be considered as a dependent province, and its expansion is intertwined with chemical sensors growth.
- *Master technologies* increase exponentially in ecosystem of sensor research. These technologies have a connective role for other technologies with an integrated-based structure by bridging and supporting the development of other inter-related technologies, such as wireless sensor network, biosensor, and fiber optic sensor. They play a vital role in integrating networks and connecting other sensor technologies to create new paths through evolution.

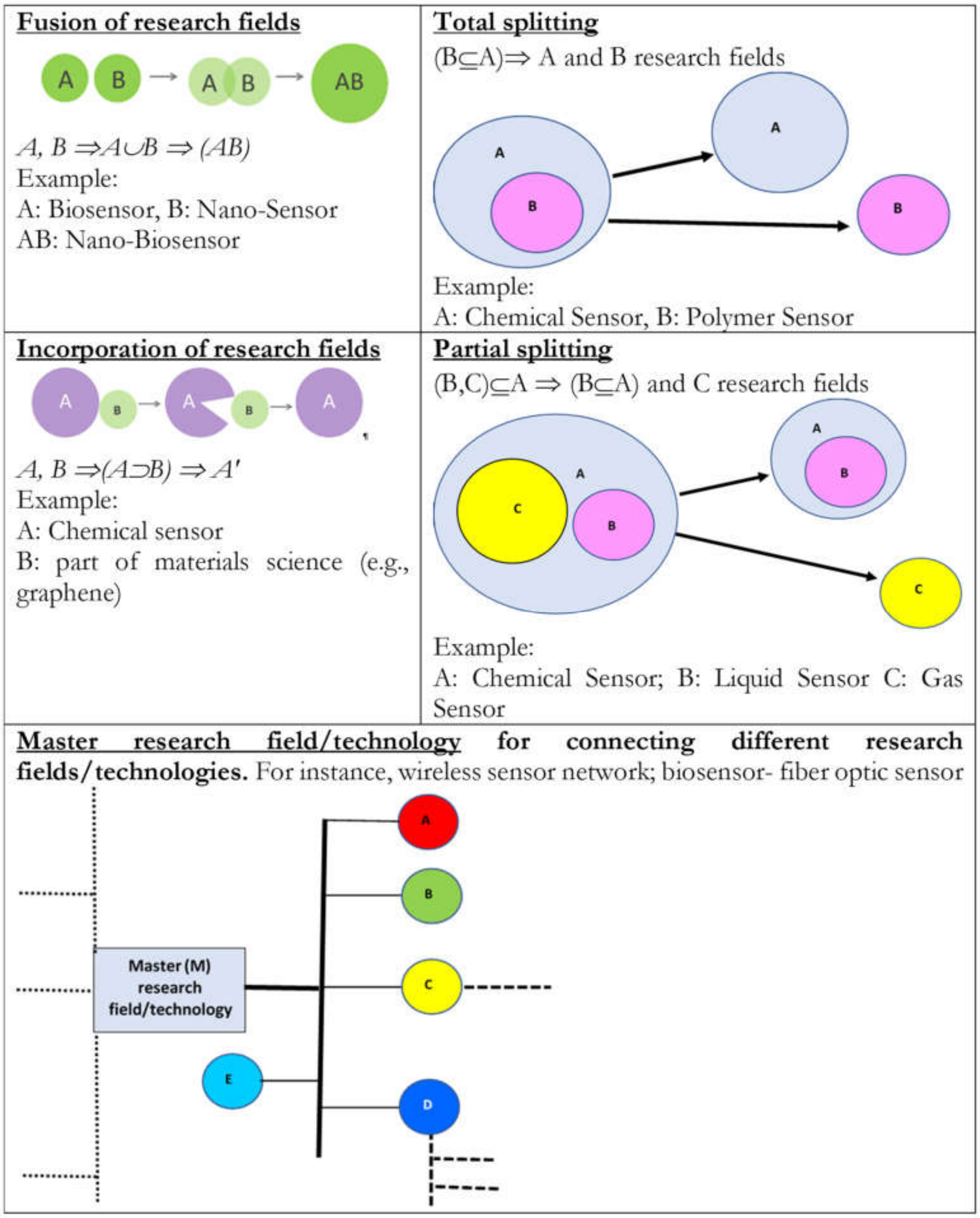

Figure 2. Patterns of evolution of science and technology based on characteristics of networks

3.6. Innovation management implications from ecosystem of sensor research and technologies

Policymakers, managers and scholars know that financial resources can be an accelerator factor of progress and diffusion of science and technology to support the scientific and technological development [17, 68]. This study provides critical innovation management implications to allocate resources with efficiency towards research fields and emerging technologies that have over time a growing degree centrality and levels of closeness and betweenness (e.g., wireless sensor networks) to foster the scientific and technological development for positive societal impact. In fact, these findings can support policymakers and funding agencies in making efficient decisions regarding sponsoring specific research fields and technological trajectories in sensors that can accelerate the development of science and technology with fruitful effects for the current and future wellbeing of people in society.

1. Conclusions, limitations and prospects

This article examines the structure and evolution of sensor networks for detecting directions of scientific and technological trajectories that are fundamental to society, science, and technology. In particular, we have used scientometric methods in order to identify the evolutionary structure of sensor technology over time. Results suggest that the evolution of the ecosystem of sensor research over the last few decades is unparalleled [1]. Sensor technologies are co-evolving with growing interactions of technological systems directed to fulfil human goals, needs and solve problems in society [62]. For instance, the evolution of smart sensors is associated with the integration of the Internet of Things, through which it is possible to connect devices and exchange information among people and systems [69]. The characteristics of evolutionary pathways in sensor research can improve the allocation of R&D investments in private and public organizations for beneficial social impact (cf., [70]). Results show that the ecosystem of sensor research is rapidly growing from 2011 to 2020 with a dense network of interconnection (cf., [61, 71]). In this period, more than 300 technologies emerged, developed and connected to others, such as "biosensor", "fiber optic sensor", "wireless sensor network", "gas sensor" and "optical sensor. Moreover, results suggest that in the last decade, sensor technologies are moving towards pathways of specialization with emerging research fields and technologies generated by a process of splitting from large research fields. For example, gas sensors are becoming more focused on "metal oxide gas sensor", "optical gas sensor", "electrochemical gas sensor", "calorimetric gas sensor", "acoustic based gas sensor", etc. "smoke sensor", "LPG sensor", "carbon monoxide sensor", "hydrogen sensor", "ammonia sensor" etc., are also the result of the development and specialization of gas sensor technologies. Consequently, industrial and manufacturing systems will be more and more directed to specialized applications of sensors. As a matter of fact, the stabilizing number of communities and the increasing level of closeness centrality in networks described indicate that the interaction between sensor technologies is more and more generating patterns based on processes of splitting that generates specialization and of merging process that captures complementary aspects of different technologies and research fields [72].

These results confirm that the science dynamics of sensor research evolves with a processes of interaction between technologies that increase the size and complexity of the ecosystem [62, 63, 65, 71, 73]. Hence, this study suggests that research fields and sensor technologies are in continuous evolution because of recent advances in inter-related information and communication technologies, artificial intelligence, internet of things, nanoscience, etc. directed to the expansion of science and society.

These conclusions are, of course, tentative. Although this study has provided some interesting, albeit preliminary results, it has several limitations. First, a limitation of this study is that sources understudy may only capture certain aspects of the ongoing dynamics of sensor research and technology. Second, there are multiple confounding factors that could have an important role in the evolution of sensor research to be further investigated in future, such discoveries, high R&D investments, collaboration intensity, openness, intellectual property rights, etc. Third, the computational and statistical analyses in this study focus on a specific period that can be extended in future investigations. Forth, sensor research associated with new technology changes borders during the evolution of science, such that the identification of stable technological trajectories and new patterns in the evolution of sensors is a non-trivial exercise.

To conclude, future research should consider new data and apply new approaches to reinforce proposed results. The future development of this study is also directed to design indices of technometrics based on measures of betweenness, closeness and degree centrality of networks to assess and predict the evolution of new technological trajectories in sensors, as well as to support implications of innovation management. An additional approach for future inquiries can be the content analysis to examine articles' content and provide a coherent understanding of hidden patterns in unanalyzed texts as part of a systematic review of literature in sensor research [74, 75-76]. Overall, then, the content analysis of articles and their systematic review with the PRISMA protocol can support an alternative understanding of sensor research and technologies [77].

Despite these limitations, the results presented here clearly illustrate the evolutionary paths of sensor research and technologies that are more and more based on growing interactions between research fields and technologies that need a continuous detailed examination for supporting technological forecasting and appropriate strategies of management of these critical technology.

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