Received: 22 July 2024 | Revised: 9 October 2024 | Accepted: 15 October 2024 | Published online: 22 October 2024

Archives of Advanced Engineering Science
2024, Vol. 00(00) 1–9
DOI: 10.47852/bonviewAAES42023902

BON VIEW PUBLISHING

RESEARCH ARTICLE

Unveiling Weak Signals of Emergence in Underwater Sensing Research Trends

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Abstract: Detecting emerging research trends is crucial as it allows for the proactive identification and monitoring of novel and influential topics in the scientific community. Monitoring research trends aids researchers, institutions, and policymakers in allocating resources, fostering innovation, and staying competitive in rapidly changing scientific landscapes. The growing significance of underwater sensing technologies in various domains has propelled research endeavors aimed at understanding the characteristics of academic discourse in this field. In this work, we comprehensively analyzed the academic research topics related to underwater sensing technologies using advanced computational methodologies. Leveraging natural language processing, topic modeling, and weak signal detection techniques, and focusing on underwater sensing as the case technology, we dissect a large corpus of scholarly articles published between 2007 and 2021 to unveil underlying thematic patterns and emergent trends within this domain while shedding light on signals of emerging technologies. Among the eighty extracted topics, six research topics were identified and recognized as emerging weak signals and validated by experts. Notably, *deep learning for underwater imaging* was the only topic that transitioned from being weak to a strong signal in the final period.

Keywords: structural topic modeling, weak signal, natural language processing, emerging research trends, underwater sensing

1. Introduction

Even though they encompass around two-thirds of the planet, the oceans often receive less attention or are disregarded compared to our primary emphasis on terrestrial and atmospheric concerns [1]. This neglect has significant implications, as the oceans are vital for global climate regulation, biodiversity, and economic resources [2, 3]. Recent progress in underwater technologies has offered new opportunities for both researchers and industries to explore the oceans further and better. For instance, challenges that were previously perceived as unsolvable due to technical constraints can now be addressed thanks to the advancements in navigation and sensing technologies in unmanned underwater vehicles (UUVs) [4, 5]. Furthermore, the emerging field of the Internet of Underwater Things (IoUT) is another example that focuses on establishing a communication framework tailored for linking underwater objects within maritime and subaquatic settings. The IoUT technology interconnects with many related application domains including intelligent ships, smart oceans, automated marine transport, positioning and navigation, underwater exploration, disaster anticipation and mitigation, and intelligent surveillance and monitoring of underwater infrastructures [6]. By establishing a robust communication framework, IoUT enhances situational awareness and facilitates proactive responses to underwater events such as natural disasters or ecological changes. It has emerged as a groundbreaking technology with the potential to create a smarter, more connected ocean environment [7].

Science and technology have emerged as primary drivers of societal and economic progress in the current era of the knowledge-centered economy. Technological advancements play a pivotal role in defining global competitiveness and are an essential necessity for fostering innovative nations. Governments and enterprises have directed their priorities toward emerging technologies, recognizing them as crucial components of technological innovation and economic growth [8]. Hence, timely identification of emerging technology trends is crucial as it allows governments and companies to promptly recognize both opportunities and potential risks, enabling the formulation of suitable research, development, and innovation strategies in response [9, 10]. However, early identification of emerging technologies is a challenging task typically manually conducted by domain experts, demanding substantial time, and effort investment to extract valuable insights [10].

The scope of this work focuses on detecting and analyzing emerging research trends within the domain of underwater sensing technologies by utilizing advanced computational techniques. Specifically, we employ natural language processing (NLP), probabilistic topic modeling, and weak signal detection to examine a corpus of academic papers published between 2007 and 2021. Integrating advanced topic modeling with weak signal detection addresses challenges inherent in existing techniques, potentially overcoming issues like signal disappearance and interpretation complexities [11]. The study not only identifies

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emerging topics but also tracks their evolution over time, providing valuable insights into the trajectory of research in this field. The main contributions of this research are as follows: (1) The automatic and quantitative nature of the analytic pipeline aims to address the limitations of existing common approaches in detecting emerging technologies, such as necessitating extensive manual intervention, and susceptibility to subjectivity due to heavy reliance on initial input from domain experts, (2) the framework not only identifies the emerging research trends it can also track evolving patterns (or patterns of interest) over time, and (3) as a case study, we analyze scientific papers published from 2007 to 2021 in the field of underwater sensing technologies to identify emerging research topic trends and extract signals.

The subsequent sections of the paper are structured as follows: Section 2 describes the data and methodology. Our findings are presented in Section 3, followed by a discussion and conclusion in Section 4. Section 5 addresses the limitations of this study and outlines potential avenues for future research.

2. Data and Methods

Figure 1 shows the data and conceptual flow of the analysis used in this study to extract emerging research topics in the field of underwater sensing technologies. The rest of this section explains the data and analytical components in detail.

2.1. Data

We extracted papers in the field of underwater sensing technologies published from 2007 to 2021 ($n = 8{,}418$), and their metadata, from Elsevier's Scopus, employing a carefully crafted search query developed by domain experts. The collected metadata encompassed various elements such as paper titles, abstracts, publication dates, author details, and their affiliations. Publications lacking titles or abstracts were omitted, and solely English-language papers were incorporated in the study.

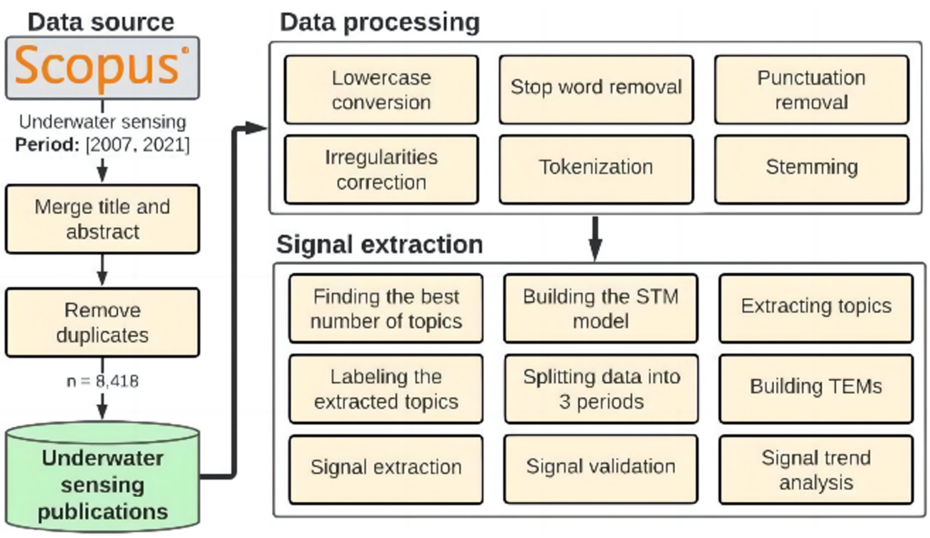
2.2. Methods

Abstracts of publications encapsulate their core content or contribution. Additionally, although they are short, titles often contain informative keywords or keyphrases not present in the abstract. Therefore, we first created a new feature by merging the title and abstract of each publication in the dataset. Subsequently, we applied a sequence of preprocessing steps to the generated feature including but not limited to conversion to lowercase, elimination of stop words, rectification of special characters, removal of punctuation, tokenization, and stemming. Next, we constructed a document-term frequency matrix wherein rows corresponded to publications, columns represented tokenized stems.

In the next step, we applied structural topic modeling (STM) [12] to extract the main research topics from the corpus. We tested several topic modeling techniques and compared their results to identify the best approach for our analysis. STM emerged as the most suitable technique due to its advantages. STM, that can be categorized under unsupervised machine learning techniques, automatically summarizes textual data by extracting latent semantic themes that encapsulate prevalent subjects. In STM, topics can have correlations, and it allows the inclusion of document-level covariates, e.g., publication date, in the topic inference process [12]. This feature facilitated the capture of temporal dynamics within the dataset, enabling the analysis of trends in topic distribution and the evolution of research projects [13]. The fact that STM incorporates inter-topic correlations sets it apart from many other mixed membership models. This property sheds light on the structural intricacies of topics at the corpus level [14]. In the output of the STM model, each publication represents a blend of topics, with the prevalence of these topics varying based on the integrated covariates.

The number of topics is a parameter that should be set in the STM model before fitting the model to the data. Relying solely on quantitative metrics to find the best number of topics may lead to less insightful model parameter choices [15]. Therefore, we first

Figure 1
The data and high-level conceptual flow of the analysis



Note: STM: Structural topic modeling, **TEM:** Topic emergence map.

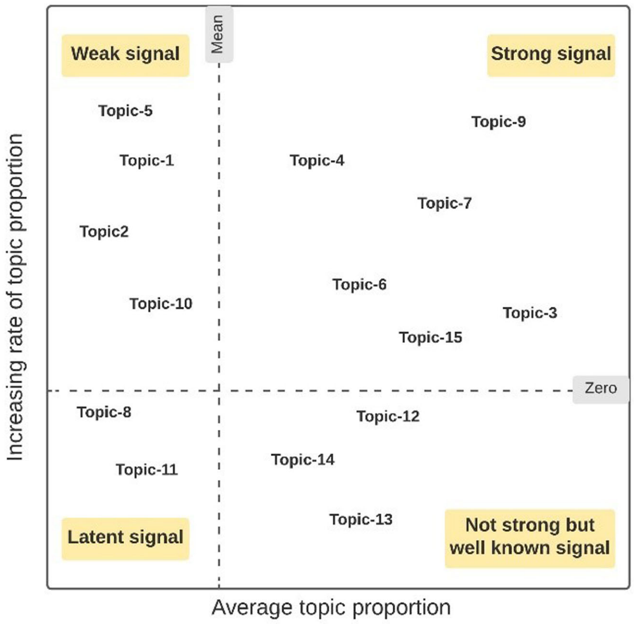
built a set of STM models by setting the number of topics in the range of (20, 150). The built models were quantitatively analyzed using four different metrics, i.e., held-out likelihood, residuals, semantic coherence, and lower bound [12]. Based on the quantitative analysis, the best number of topics was found to be in the range of (77, 81). Next, these five models were qualitatively assessed by examining their representative keywords and documents, focusing on the coherence of representative terms within each topic, the relevance of top representative documents to their corresponding topics, and the absence (or at least limited) of overlap between topics within a single model. Following the mentioned semi-automatic approach, the number of topics was set to 80.

Similar to other common topic modeling techniques, STM does not produce a label for the extracted topics automatically and topics are attributed with a set of keywords. This poses challenges in interpreting the topics. We employed a multi-step process to automatically create indicative labels for the extracted topics. The labeling steps were as follows: (1) selecting a random set of papers for each topic, (2) summarizing the chosen papers using a pre-trained Text-To-Text Transfer Transformer (T5) model [16], (3) compiling the summaries, (4) utilizing a pre-trained T5-based headline generator to create a representative title for the combined summaries, and (5) iterating through steps 1 to 4 fifteen times to generate fifteen representative labels per topic. To ensure the fidelity of the extracted topics and their relevance to the examined field, the automatically generated labels were reviewed and validated by domain experts. Subsequently, a single topic label was assigned to each topic.

After extracting and labeling topics, we employed the weak signal analysis framework to identify signals of emerging research topics. We split the data into three five-year intervals, i.e., P_1 = (2007, 2011), P_2 = (2012, 2016), and P_3 = (2017, 2021), and aimed to investigate potential statistical variations in extracted research topics between these periods. Ansoff [17] introduced the concept of weak signals as a counterpoint to strong signals, suggesting that relying solely on strong signals in formulating future strategies could lead to crises due to unforeseen changes. Holopainen and Toivonen [18] elaborated on Ansoff's definition, emphasizing weak signals as indicators of potential future changes, urging their use as warnings or indications of new opportunities. Yoon [19] proposed a quantitative framework based on text mining to address the limitations inherent in qualitative approaches. Drawing from the weak signal concept, Yoon's approach extracted weak and strong signals by analyzing word frequency, document occurrences, and temporal frequency change rates. To address the limitations of the term-based approaches (e.g., the need for manual intervention, loss of information, low interpretability), in this work, we followed Park and Kim's approach [11], and instead of relying on word and document frequencies, we utilized topic proportions obtained from the STM model to produce the signals of emerging research topics. Signals are extracted via building a topic emergence map (TEM).

Figure 2 demonstrates a sample TEM in which the x-axis represents the average topic proportions extracted from the STM model and the y-axis represents the increasing rate of the topic proportion. This methodology offers a resolution to the issue of potentially missing keywords by integrating topic proportions and enables a more comprehensive interpretation of signals by focusing on topics rather than keywords. TEM is divided into four quadrants based on the mean of values on the x-axis and zero on the y-axis, resulting in four quadrants as follows: (1) The top-right region denotes **strong** signals, comprising research topics with high average proportion and a high growth rate, (2) the top-left

Figure 2
Topic emergence map (TEM)



area represents **weak** signals, encompassing topics with low average proportion but high growth rate, (3) terms in the bottom-left zone are classified as **latent** signals, and (4) the bottom-right area of the TEM characterizes signals that are **not strong but well-known**. In Figure 2, for example, topic-1 is identified as weak, topic-4 as strong, topic-8 as latent, and topic-12 as not strong but well-known signal. Using these regions, we attributed a signal label to each topic in the TEM across each examined period, i.e., P_1 to P_3.

3. Results

3.1. Topics

As detailed in Section 2.2, STM [12] was employed to derive 80 research themes from the compiled underwater sensing publications. Table 1 lists the extracted topics along with their normalized proportions. Among the extracted topics, Topic 80, labeled as "Mathematical modeling of underwater sensor networks", and Topic 71, labeled as "Underwater image processing", have the lowest and the highest proportions, respectively.

3.2. Topic correlations

A topic correlation analysis was conducted to explore the associations among the derived topics and identify topics that are prone to appearing together within the same publication. As seen in Figure 3, the majority of the identified topics exhibit negative correlations, indicating an unlikelihood of co-occurrence within the same set of publications. This separation may imply that the research within the field of underwater sensing tends to specialize, with publications focusing on distinct areas without significant overlap.

In contrast, a few topic pairs display no correlation, indicating they are neutral with regard to co-occurrence, and a small subset of

Table 1
Extracted topics' labels and their normalized proportion (prp)

No	Topic label	Prp
1	Underwater Optical Imaging	0.49
2	Underwater Sensor Networks	3.43
3	Underwater Navigation System	1.61
4	Intelligent Navigation for Underwater Vehicles	1.12
5	Underwater Laser Image Target Detection	1.63
6	Ocean Monitoring, Marine Mammal Communication	0.92
7	Marine Security	0.85
8	Chinese Navy	0.60
9	Submarine Tracking Control System	0.75
10	Submarine Warfare	1.17
11	Future of Defense	0.76
12	Underwater Wireless Sensor Networks	2.14
13	Energy-Efficient Communication	2.87
14	Improving the Performance of Underwater Sensors	2.00
15	Ocean Environment Surveillance System	1.10
16	Underwater Image Reconstruction and Improvement	2.18
17	Sea Clutter	0.60
18	Airborne Radar Sensor Systems	1.30
19	Monitoring of Water Quality	0.75
20	Detecting Objects in Water	0.87
21	Monitoring Submerged Structures, Plants, Vehicles	0.60
22	Tracking Underwater Objects	0.73
23	Submarine Fin Tip Vortex	0.47
24	Submarine Track Management	0.74
25	Detecting Underwater Mines	0.79
26	Improving Quality of Service	0.45
27	Deep Learning for Underwater Object Detection	1.83
28	Underwater Robotic Intervention Systems	0.92
29	Nuclear Radiation Detection Systems	0.42
30	Underwater Target Positioning	1.45
31	Computer Vision for the Identification and Recognition of Subsea Targets	1.13
32	Routing Protocols for Underwater Sensor Networks	1.11
33	Underwater Magnetic Target Detection	1.41
34	Underwater Acoustic Communication	3.06
35	Internet of Underwater Things	0.74
36	Underwater Laser Detectors	1.86
37	Effect of Explosives on Marine Environments and Structures	0.73
38	Time Synchronization in Underwater Sensor Networks	1.17
39	Medium Access Controls (MACs) in Underwater Sensor Networks	2.82
40	Subsea Cable Monitoring	0.36
41	Underwater Sonar Imaging	0.82
42	Oil Spill Detection	0.54
43	Cyber Defence	1.17
44	Cooperative Positioning in Underwater Sensor Networks	1.03
45	Underwater Sensor Network Localization	1.90
46	Routing for Underwater Sensor Networks	1.55
47	Ocean's Ecosystem and Climate Change	0.88
48	Monitoring Seafloor Deformation	0.80
49	Deep Learning for Underwater Imaging	1.63
50	Marine Biology	0.58
51	Underwater Target Tracking	1.95
52	Underwater Communication Systems	1.09
53	Ship Biofouling Inspection	0.21
54	Underwater Imaging	1.01
55	Detecting and Locating of Underwater Vehicles	0.99
56	Remotely Operated Underwater Vehicles	0.88
57	Monitoring Marine Environment, Pollution, Leaks	0.40
58	Clustering Mechanisms for Underwater Sensor Networks	1.02
59	Monitoring Subsea Water Quality	0.79
60	Ship Detection	0.94
61	Novel Underwater Sensor Networks	1.40
62	Military, Naval Multi-role Helicopters	0.93
63	Data Collection Networks	1.63
64	Optical Fiber Sensors	1.08
65	Tracking Ocean Current Fields	1.26
66	Underwater Wireless Optic Communication	1.31
67	Crypto-Blockchain-Based Approaches for Underwater Sensor Networks	0.84
68	Underwater Image Restoration Techniques	3.79
69	Coverage Enhancement of Sensor Networks	2.30
70	Underwater Image Enhancement	1.74
71	Underwater Image Processing	4.30
72	Data Delivery in Underwater Sensor Networks	2.76
73	Robotic Underwater Vehicles	1.04
74	Ultrasonic Transmitting Systems	0.86
75	Anomaly Detection, Maritime Traffic Monitoring	1.57
76	Submarine Signals	1.59
77	Submarine Magnetic Detection	0.50
78	Biosensor Underwater Detection	0.49
79	Crack Detection Systems	0.35
80	Mathematical Modeling of Underwater Sensor Networks	0.15

*The top 10 topics with the highest proportion are bolded.

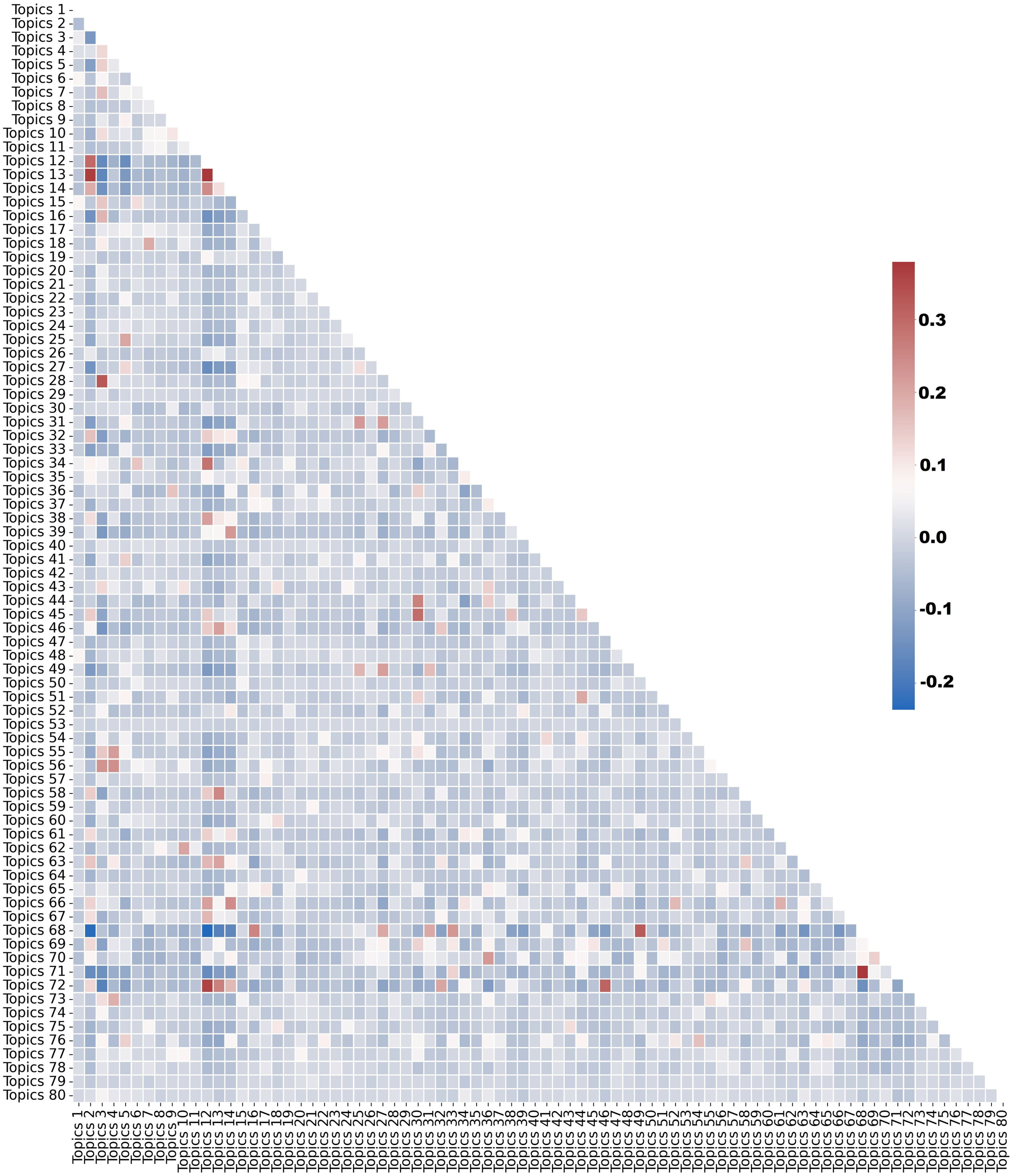
topics exhibits positive correlations, suggesting that these topics may frequently appear together in the same body of research. The top three pairs with the highest positive correlation in descending order are (Topic 12, Topic 13), (Topic 68, Topic 71), and (Topic 2, Topic 13).

The correlation between Topic 13 (energy-efficient communication) and Topic 2 (underwater sensor networks), along with Topic 12 (underwater wireless sensor networks), forms an expected structural cluster, highlighting the importance of energy-efficient communication in underwater sensing technologies. This correlation may reflect the emphasis within the underwater sensing research community on optimizing communication protocols to conserve energy, a critical factor given the limitations in power resources for underwater sensor technologies. The prominence of these topic clusters may highlight that energy efficiency remains a core concern in the development of underwater wireless sensor networks, underscoring its importance in enhancing network performance and longevity.

3.3. Emerging weak signals

Table 2 lists the research topics identified as weak signals in at least one of the examined periods, i.e., P_1, P_2, and P_3, along with their signal trend over time. Overall, six out of the 80 topics were identified as weak signals in at least one of the periods. In the

Figure 3
Correlations between extracted topics



table, numbers in parentheses indicate the count of publications where the particular topic has been dominant. Topic 17, discusses sea clutter in marine environment that emerges when radar beams encounter waves and sea spray across lakes, seas, and oceans. In marine radar target detection, sea clutter complicates radar operations by generating noise and false echoes, thereby affecting the accuracy of the system. The growing interest in this topic may reflect the need for improved radar technologies that can mitigate the challenges posed by sea clutter. Topic 26 discusses improving the quality of service (QoS) (awareness) in underwater sensor networks. This is critical to ensuring the efficient, reliable, and timely collection and transmission of data in underwater

Table 2
Research topics identified as weak signals in at least one of the examined periods along with their temporal signal trend

No	Topics	2007–2011 (P_1)	2012–2016 (P_2)	2017–2021 (P_3)
17	Sea Clutter	Weak (6)	Latent (9)	Latent (9)
26	Improving Quality of Service		Latent (4)	Weak (5)
36	Underwater Laser Detectors	Latent (9)	Latent (7)	Weak (12)
49	Deep Learning for Underwater Imaging	Weak (5)		Strong (146)
53	Ship Biofouling Inspection		Weak (5)	Weak (6)
62	Military, Naval Multi-role Helicopters	NSWK (77)	Latent (8)	Weak (3)

*The number within parentheses signifies the count of publications where the particular topic has been predominant.

environments, and may involve addressing issues such as latency, communication reliability, and energy efficiency. Topic 36 covers underwater laser detectors and associated areas like coverage degrees and identifying the optimal path for UUVs in searching submarines. This may indicate a growing interest in integrating laser detection systems with autonomous underwater vehicles (AUVs), advancing their role in both civilian and military operations. Topic 49 explores the application of deep learning (DL) techniques in underwater imaging, covering various tasks such as target recognition, image classification, and segmentation. DL's ability to handle complex, noisy, and often incomplete data, typical in underwater environments, makes it a powerful tool for enhancing image quality and extracting meaningful information. Topic 53 addresses ship biofouling inspection (SBI) and related areas such as the design and development of remote vehicle prototypes for SBI. SBI refers to the inspection and monitoring of the accumulation of marine organisms on the hulls of ships and other submerged structures. Topic 62 involves discussions on the military and defense sector, particularly focusing on navy multi-rope helicopters. These helicopters provide flexibility and support for a variety of naval missions. The emergence of this topic as a weak signal may point to ongoing research into optimizing the design and capabilities of these helicopters to better meet the evolving demands of modern naval warfare.

As seen in Table 2, among the weak signal topics, only Topic 49 (DL for underwater imaging) transitioned from being weak in P_1 to strong in P_3. The growing application of DL techniques in underwater imaging could be due to its ability to handle complex data patterns, enabling enhanced image processing and feature recognition in challenging underwater environments. Additionally, DL algorithms in general, offer improved accuracy and efficiency in analyzing vast amounts of image data, which could foster advancements in underwater exploration and research. The high number of publications about Topic 49 in P_3 ($n = 146$) also indicates the high and growing interest of the research community in this interdisciplinary topic. In the transition from P_2 to P_3, Topics 26, 36, and 62 shifted from latent to weak signal. QoS in underwater sensing technologies refers to the capability of these systems to provide reliable, efficient, and timely delivery of data and services while maintaining a certain level of performance. Improving QoS (Topic 26) may involve various aspects such as the accuracy of data collection, reliability of communication links, latency in data transmission, energy efficiency, robustness of the sensing equipment, and the ability to adapt to the challenging underwater environment. Underwater laser detectors (Topic 36) are sensing devices that utilize laser beams to detect and measure objects, substances, or conditions underwater. These detectors have various applications in underwater exploration and are crucial in studying underwater ecosystems. Naval multi-role helicopters (Topic 62) are specialized helicopters used by naval forces equipped with multiple rope systems for various maritime operations. These helicopters are designed to support naval missions such as anti-submarine warfare, search and rescue, maritime surveillance, cargo transport, and personnel transfer.

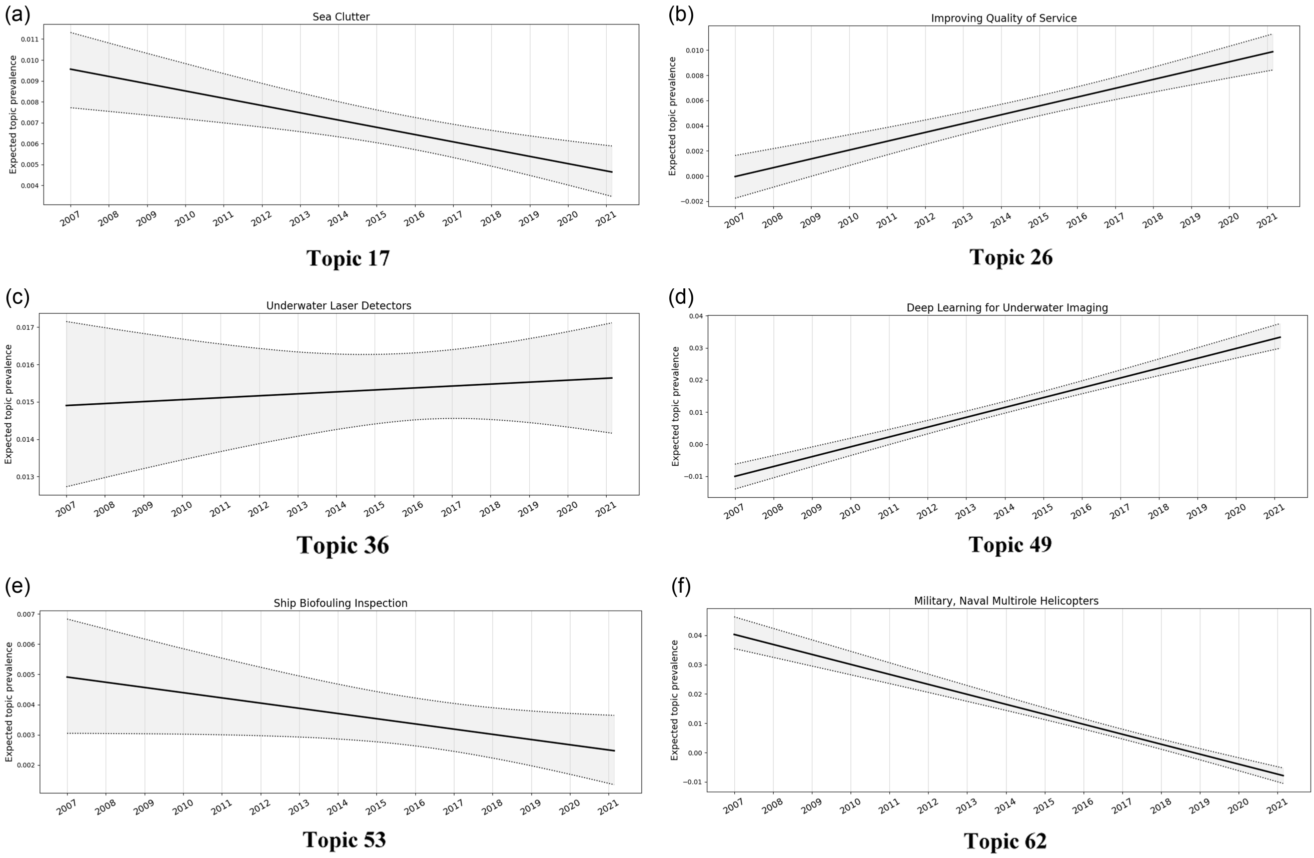
Figure 4 shows the expected prevalence of the extracted weak signal topics over time. Shaded areas in the figure indicate 95% confidence intervals. During the examined period, Topic 49 (DL for underwater imaging), Topic 26 (improving QoS), and Topic 36 (underwater laser detectors) displayed an upward trend. Notably, the increase was more pronounced for the first two topics. Given the narrow confidence intervals associated with Topics 49 and 26, it is more probable that these topics will continue to grow in the upcoming intervals. Among the weak signal topics identified, Topic 17 (sea clutter), Topic 53 (SBI), and Topic 62 (military, naval multi-role helicopters) showed a decline in their trends. The latter topic is anticipated to persist in its decline, given its steep slope and narrow confidence interval, whereas the other two topics might also continue their decreasing trends in the upcoming interval.

4. Discussion and Conclusion

In this study, we used a combination of techniques including topic modeling, NLP, and weak signal analysis to examine a large collection of papers published from 2007 to 2021. This approach allowed us to pinpoint emerging research areas within the domain of underwater sensing technologies, as a case technology. The data were divided into three distinct five-year intervals, i.e., P_1 = (2007, 2011), P_2 = (2012, 2016), and P_3 = (2017, 2021) to explore potential statistical differences in the identified research topics across these periods and reveal any underlying temporal trends or patterns.

Eighty research topics were extracted from the corpus and in total, six out of the 80 topics were recognized as weak signals within at least one of the periods under consideration (Table 2). There is an expectation that some weak signals may evolve into strong signals in the future, although not all weak signals necessarily transform into strong ones [11]. Within this group of six topics, Topic 49 (DL for underwater imaging) stood out as the sole topic that transformed into a strong signal during the last period. This is noteworthy as there has been a growing interest in applying machine learning and DL techniques in various domains from healthcare (e.g., [20, 21]) and drug discovery (e.g., [22, 23]) to political and social sciences (e.g., [24, 25]) and literature mining (e.g., [26]). This is due to the continuous advancements in DL algorithms, coupled with the availability of vast amounts of digital data and high-performing computers. The burgeoning interest in employing DL techniques for underwater imaging

Figure 4
Temporal progression of emerging research topics (shaded regions between the dotted lines represent the 95% confidence interval)



arises from their capability to enhance image processing and analysis in challenging underwater environments. These techniques offer improved accuracy in recognizing underwater features, aiding in tasks such as object detection [27], scene understanding [28] and classification [29], and navigation [30] in the aquatic domain. Our findings also indicate a continued expansion in the utilization of DL techniques for underwater imaging (Figure 4).

In the final period (P_3), four topics emerged as weak research topics, i.e., Topics 26 (improving QoS), 36 (underwater laser detectors), 53 (SBI), and 62 (military, naval multi-role helicopters). During the transition from the P_2 to P_3 period, three research topics, i.e., Topics 26, 36, and 62, shifted from being latent signals to weak signals. Underwater laser detectors (Topic 36) are utilized for their ability to emit laser beams into the water, enabling the measurement and detection of various underwater features and substances. They find applications in various tasks such as mapping coastal areas, analyzing water composition, monitoring ocean ecosystems, and identifying objects for autonomous navigation [31]. Therefore, this field may continue to be an actively researched subject (Figure 4) due to its potential for enhancing underwater exploration, providing high-precision data collection, and supporting advancements in underwater research, marine conservation, and industrial applications. Naval multi-role helicopters (Topic 62) can be used for several maritime operations, e.g., facilitating the deployment and retrieval of various sensors, equipment, and instruments into underwater environments for tasks such as sonar deployment, and underwater exploration. The declining trend observed for this research topic might be attributed to advancements in AUVs, which offer more cost-effective and efficient alternatives for underwater operations and have received a lot of attention [32]. Topic 53 (SBI) emerged as a weak research topic during the P_2 period and maintained its status throughout the final period. This topic involves assessing and managing the accumulation of organisms on a ship's hull, which can affect vessel performance and can have environmental impacts. Various sensors and imaging techniques are utilized to detect, monitor, and analyze the extent of biofouling on submerged surfaces of ships. The emergence of SBI as a weak signal might be due to its significant impact on vessel fuel efficiency, transportation costs, and ecological consequences [33].

The methodology employed in this study is applicable beyond underwater sensing technologies to analyze trends across various fields using massive publication data. Access to large-scale textual data enables this approach to offer a fundamental comprehension of research topic changes within that domain. Except for the publication search query, which requires subject-matter expertise, the rest of the approach can be automated, including the labeling of topics (a task traditionally reserved for experts in the technology area of interest [10]). For that reason, we believe this approach holds substantial advantages for organizations that are involved in technology foresight and road-mapping and can serve as an additional tool to guide their research and development endeavors.

5. Limitations and Future Work

While this study provides valuable insights into emerging research trends in underwater sensing technologies, several limitations should be acknowledged. The analysis was conducted using a specific dataset comprising scholarly articles published between 2007 and 2021. Although this timeframe allows for a comprehensive examination of trends, it may not capture the most recent developments or emerging technologies in the field beyond 2021. Although various topic modeling techniques were tested, the selection of the most appropriate model can depend on the data and research objectives. The results may be influenced by the chosen parameters and the inherent limitations of the algorithms used. Further validation with additional datasets could enhance the reliability of the findings. The study primarily emphasizes quantitative analysis of research topics, potentially overlooking qualitative aspects of the discourse in underwater sensing technologies. Insights from qualitative analysis could provide a deeper understanding of the implications of these emerging trends. By addressing these limitations, subsequent research can further enrich the understanding of underwater sensing technologies and their evolving landscape.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Ashkan Ebadi: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Alain Auger:** Conceptualization, Validation, Writing – review & editing. **Yvan Gauthier:** Validation, Writing – review & editing.

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How to Cite: Ebadi, A., Auger, A., & Gauthier, Y. (2024). Unveiling Weak Signals of Emergence in Underwater Sensing Research Trends. *Archives of Advanced Engineering Science*. https://doi.org/10.47852/bonviewAAES42023902