A Systematic Literature Review on Long-Term Localization and Mapping for Mobile Robots*

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Abstract

Keywords: simultaneous localization and mapping (SLAM), lifelong SLAM, long-term autonomy, mobile robots.

1 Introduction

2 Purpose of the study

2.1 Limitations of current studies

Table 1: Existent Literature Reviews, Surveys, and Tutorials on SLAM.

Topic	**Reference**
Probabilistic approaches and data association	Bailey and Durrant-Whyte 2006; Durrant-Whyte and Bailey 2006
SLAM back end	Grisetti et al. 2010
Multi-robot SLAM	Saeedi et al. 2016
Visual odometry	Fraundorfer and Scaramuzza 2012; Scaramuzza and Fraundorfer 2011
Overview of challenges in SLAM	Cadena et al. 2016
Trends in SLAM for autonomous vehicles	Bresson et al. 2017
Completar tabela!	

2.2 Motivations and goals

Research question: What is the current state of the art of long-term localization and mapping using mobile robots?

Goals of this review:

- which are the main strategies for accomplishing long-term operations with mobile robots;
- how to deal with varying conditions of the environment;
- how do autonomous robots deal with the dynamics of the environment;
- which are the main strategies to deal with the limited computational resources of a mobile robot on long-term operations.

PICO framework (Population–Intervention–Comparison–Outcome) helps to frame the research questions of this systematic review into a more structured framework:

- **Population:** mobile robots;
- **Intervention:** localization, mapping, SLAM;
- **Comparison:** *not applicable to this study*;
- **Outcome:** long-term operation, lifelong autonomy, robust.

3 Methodology

A systematic literature review uses explicit, rigorous, and reproducible systematic methods to synthesize the findings of studies related to a particular research question, topic area, or phenomenon of interest. This type of review assures the quality and trustworthiness of the review's findings by presenting a complete, organized, and summarized analysis of all works considered while allowing others to replicate or update the reviews. The most common standard for performing a systematic review is the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) (Page et al. 2021) statement. Although the PRISMA statement has been designed originally for evaluating the effects of health interventions, the checklist items of the methodology are general and applicable to other subject areas. Thus, the methodology used in this systematic review follows the PRISMA (Page et al. 2021) guidelines.

This section presents the detailed methodology used in this study. First, the eligibility criteria decide which studies to include in the review. Next, the search strategy details the information sources considered in the review and the base string and search fields used for inquiring these sources. Furthermore, the selection process focuses on describing its stages and the quality evaluation criteria used to select works for the synthesis and analysis phase of the review. Lastly, the data extraction process details the relevant data collected for synthesis and analysis. Parsifal (Freitas 2014) is the online tool used to support the literature review in designing the methodology protocol, removing duplicates, screening and selecting works including their quality assessment. Additional documentation and scripts developed within the scope of this review related to removing duplicates, checking and processing the bibliographic references, and data extraction are available in a public GitHub repository[1].

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[1] https://github.com/sousarbarb/slr-ltlm-mr

3.1 Eligibility criteria

Table 2 presents the exclusion criteria used to determine the eligible studies for the selection process. These eligibility criteria focus mainly on the type of paper and availability. The index criterion rejects all publications not indexed in a scientific publication venue. This rejection guarantees that the eligible works were peer-reviewed by the scientific community. Also, the exclusion criteria reject short papers and gray, secondary, and tertiary literature. Short papers do not usually present a detailed methodology of their scientific contribution. As for only considering primary literature in the review, this criterion increases the relevance of search results by favoring original articles and simultaneously guaranteeing peer-revision of the works. In terms of language, only considering studies with English full-texts increases the scope and visibility of the review. Similarly, the eligibility criteria reject studies not available in digital libraries for reproducibility and accessibility reasons.

Table 2: Exclusion criteria for the selection process.

E#	Criteria	Statement
E1	Index	Papers not indexed in a scientific publication venue
E2	Language	Full-text of the papers not published in English
E3	Subject Area	Papers not classified in the databases as Computer Science, Engineering, Mathematics, or Multidisciplinary
E4	Short Papers	Papers classified as short papers accordingly to the publication venue
E5	Gray, Secondary, and Tertiary Literature	Books, preprints, reports, reviews, thesis, ...
E6	Availability	Full-text of the papers not available in digital libraries
E7	Dataset	Papers that focus only on data collection
E8	Coverage	Papers using only odometry for localization
E9	Scope	Papers that focus on different and not related subjects

Another exclusion criterion considered in the review is relative to the studies' categorization of their subject areas by bibliographic databases. The ones considered in the review are Computer Science, Engineering, Mathematics, or Multidisciplinary areas. In the list provided by the Clarivate's Journal Citation Reports[2], these four subject areas include the artificial intelligence, interdisciplinary applications, electrical and computers engineering, robotics, and applied mathematics categories, among others. These categories are intrinsically related to the localization and mapping problem for long-term operation of mobile robots.

The final three criteria presented in Table 2 focus on the scientific contribution of the studies. The dataset criterion rejects all works that focus only on sharing a data collection. Although these works are important for the evolution of localization and mapping algorithms in providing a benchmark for comparison and reference purposes, their scientific contribution is not directly comparable to research articles. Odometry-only approaches are unusable over long distances invalidating their use for long-term operations with mobile robots. As for the scope criterion, this review does not consider eligible for selection papers not related to long-term localization and mapping.

3.2 Search strategy

The search phase consists of identifying the data sources that could be relevant for this literature review, and defining the base string and which search fields considered to obtain the results for the review. *Web of Science* and *Scopus* are traditionally the two most widely used bibliographic databases. However, previous studies demonstrate that different databases differ significantly in their scientific coverage (Mongeon and Paul-Hus 2016; V. K. Singh et al. 2021). Thus, the data sources considered in this review are the following ones: *ACM Digital Library*, *Dimensions*, *IEEE Xplore*, *INSPEC*, *Scopus*, and *Web of Science*.

Moreover, May 17, 2022, is the date of the last full inquiry. Future reviews on the topic of this study should consider this final date as theirs initial one. As for inquiring the data sources, the base string used is the following one:

```
(robot* OR vehicle*)                              AND
((locali* AND map*) OR "slam")                    AND
("long term" OR "life long" OR lifelong)
```

The first terms, `robot* OR vehicle*`, attempt to focus the search results to the desired population. These two terms have multiple synonyms within the scope of autonomous mobile robots: mobile robots, autonomous vehicles, robotics, agricultural robots, intelligent robots, service robots, unmanned aerial/ground/underwater vehicles, among other terms. Therefore, by adding the asterisk to the end of the terms robot and vehicle (`robot*` and `vehicle*`, respectively), and by only considering the terms with asterisk in the inquiry, all the synonyms are covered for the desired population. Given the incompatibility of the *Dimensions* database with wildcards (e.g., using the asterisk), the first part of the base string becomes as follows when searching in this database: `robot OR robots OR robotics OR vehicle OR vehicles`.

The next part of the query focus on the intervention side of the systematic review. Given the interest of this review on searching for localization and mapping algorithms, `locali*` and `map*` summarize all the synonyms for the localization and mapping terms, respectively. For example, `locali*` not only is agnostic to the US versus UK spelling differences (localization vs localisation, respectively) but also resumes several synonyms: localization, localize, or localizing. The term `map*` also attempts to cover its respective synonyms such as map, maps, or mapping. Also, the acronym `"slam"` is another alternative to search for localization and mapping algorithms. Even though its definition is compatible with `locali* AND map*`, some authors only refer to SLAM. Similarly to the inquiry's first part, the second one becomes as follows for searching in *Dimensions*: `((localize OR localization OR localizing OR localise OR localisation OR localising) AND (map OR maps OR mapping)) OR "slam"`.

As for `"long term" OR "life long" OR lifelong`, this part of the base string is relative to the outcome of the PICO framework, presented in Section 2. The reason for having both `"life long"` and `lifelong` terms is the existing confusion in which term is grammatically the correct one.

Furthermore, the Title, Abstract, and Keywords are the fields considered for obtaining the search results. The third one includes the author keywords, the indexed terms by the databases, and the uncontrolled ones if they are available. The selection of these search fields for this review improves the relevance of the results compared to using all fields and the full text by focusing the search on the summary items of the works. Indeed, the main contributions of scientific works should be summarized in at least the title, abstract, or the author keywords. The indexed terms also help in obtaining records only related to the base string used

[2] https://jcr.clarivate.com/jcr/browse-categories

in this review. However, not all data sources have available the search fields considered in the review or some of them require an adaptation when performing the search. Although the *ACM Digital Library* allows searching within multiple search fields, including the ones considered in this review, the advanced search query on this library sets by default an AND operator between the different fields. This setting must be changed manually in the query syntax to the desired OR operator. Also, there are two options to search items in the *ACM Digital Library*: *The ACM Full-Text Collection* and *The ACM Guide to Computing Literature*. Given that the latter includes all the content from the former, the identification process in this source performs the search using *The ACM Guide to Computing Literature* option. Other than searching in the publications' full data, *Dimensions* only has the title and abstract search fields compatible with this review. Given the limitation of *IEEE Xplore* to 7 wildcards, the search results of this digital library using the base string for the inquiry are the grouping of different searches considering only a search field at a time, importing each search results to Parsifal and removing the duplicates. As for *INSPEC*, *Scopus*, and *Web of Science*, these databases have available all the search fields considered in the review.

In terms of the publication date, this review does not restrict it to avoid ignoring important works and to improve the discussion. Indeed, to best of the authors knowledge, there is not available a systematic review on long-term localization and mapping for mobile robots to provide an initial date for rejecting older publications. Even though the number of publications per year could indicate an initial date on when the topic gained relevance, the date filtering could still reject important works.

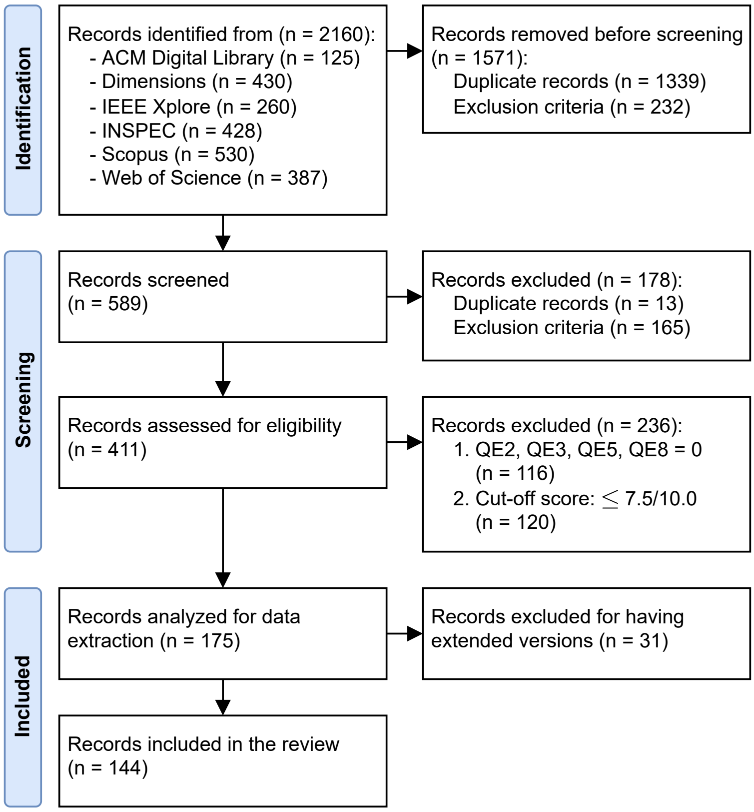


Figure 1: PRISMA flow diagram for the selection process.

3.3 Selection process

The selection process of this review summarized in Figure 1 has three phases: identification, screening, and quality assessment. The first phase consists of inquiring each data source discussed previously with the base string and adapting it if needed. The second phase requires screening the papers. In this review, screening is equivalent to reading the publications' title and abstract and deciding whether the study is eligible or not based on the exclusion criteria. Then, a set of evaluation criteria assesses the quality of the eligible records. The records obtained after the three phases of the selection process are for the data extraction phase.

3.3.1 Identification

In the identification phase of this review, the search strategy is applied to all data sources. *ACM Digital Library*, *Dimensions*, *INSPEC*, *Scopus*, and *Web of Science* data sources only require a single inquiry to obtain the search results. Given the limitation of the *IEEE Xplore* for using wildcards mentioned in Section 3.2, the number of records for this source presented in Figure 1 represents the results of 7 inquiries (using the fields title, abstract, author keywords, IEEE terms, INSPEC controlled terms, and the INSPEC uncontrolled ones, respectively) after removing the duplicates with the support of Parsifal. Although the total number of search results found is 2160, Parsifal is used to remove duplicates from different data sources, excluding 1339 records. Following the duplicates removal, the exclusion criteria defined in Section 3.2 exclude 232 works from the review. This exclusion is possible due to *INSPEC*, *Scopus*, or *Web of Science* having filters related to the publication's type, subject area, and language.

The works excluded from the search results also include the ones that do not meet the exclusion criteria E4 and E7. For the first one, a Python script available in the GitHub repository of this review searches studies with a number of pages lower or equal to 4. Even though short papers have a maximum number of 3 pages, the papers with 4 pages do not usually present a detailed methodology. As for the E7 exclusion criterion, some works are possible to remove from the review by searching in their title for the term "dataset". All excluded articles of this review are double-checked to certify if the exclusion criteria are correctly applied. For example, articles published in the Remote Sensing journal from MDPI do not meet the E3 criterion. Indeed, the Journal Citations Reports from Clarivate classifies it by the following categories: Remote Sensing, Geosciences Multidisciplinary, Environmental Sciences, and Imaging Science & Photographic Technology. However, most search results from this journal found in the identification phase are directly related to the topic of this review and the respective subject areas. Thus, in these cases and in other ones related to the remaining exclusion criteria, the decision is reverted to consider the initially rejected studies for the next phase of the review.

3.3.2 Screening

Next, the screening phase in this review consists of reading the title and abstract of the publications and rejecting the ones that meet the exclusion criteria. However, the initially rejected papers have another assessment for validating the exclusion. The analysis of the results and conclusions of these publications considering the exclusion criteria either confirms the exclusion decision or reverses it to eligible works for quality assessment. As a result of the screening phase, 178 studies are rejected from the initial identified 589 works. The duplicate records found in screening and removed manually are due to titles with invalid characters originated by exporting the search results from the *Dimensions* database.

3.3.3 Quality assessment

The quality evaluation in this review of the selected works from screening follows the 8 Quality Evaluation (QE) criteria presented in Table 3. All of them are subjective criteria derived from the analysis of the eligible works. The score column establishes the possible values for the QE criteria, in which the minimum, intermediate, and maximum values correspond to none, partial, and full compliance, respectively. Furthermore, QE1, QE2, QE4, and QE8 focus on the details provided in the papers, specifically, if the discussion of the related work, the proposed methodology, the experimental setup, and the results are detailed and thoroughly analyzed in the publication, respectively. The possible scores for QE3 are twice the value of QE1, QE2, QE4, and QE8 due to this criterion being directly related to the topic of the review. A work focusing on both localization and mapping problems will have a score of 2.0 (full compliance). If the study only focuses on one of these problems or none of them, the scores will be 1.0 or 0.0, i.e., partial or no compliance, respectively. QE5 evaluates the long-term results of the eligible studies and is either 2.0 (full) or 0.0 (no compliance). This criterion has the same range as QE3 for similar reasons, given the focus of this review on long-term localization and mapping algorithms. The definition of long-term experiments for assigning full compliance in QE5 is the following one: dynamic changing environments (e.g., dynamic elements or semi-static ones), increasing environments or feature maps in terms of their size, redundant data removal, or varying conditions (e.g., different seasons of the year or lighting conditions). QE6 and QE7 can only be 1.0 or 0.0. The former criterion intends to highlight works that compare themselves to the state of the art and/or ground-truth data. The latter emphasizes the importance of having available either the implementation of the proposed methodology or the data used in the experiments for other works to be able to compare the proposed methodologies. Lastly, considering the possible scores for the QE criteria in Table 3, each work can only have a maximum score of 10.0.

Table 3: Quality evaluation criteria and score range.

QE#	Criteria	Score
QE1	Does the paper have an updated state of the art on long-term localization and mapping?	{0.0, 0.5, 1.0}
QE2	Is the methodology appropriate and detailed?	{0.0, 0.5, 1.0}
QE3	Does the methodology consider both localization and mapping problems?	{0.0, 1.0, 2.0}
QE4	Is the hardware and/or software used in the experiments detailed?	{0.0, 0.5, 1.0}
QE5	Does the paper presents any kind of long-term experimental results?	{0.0, 2.0}
QE6	Does the paper presents comparative results with other methods and/or ground-truth data?	{0.0, 1.0}
QE7	Does the work's implementation and/or the data used in the experiments are publicly available?	{0.0, 1.0}
QE8	Is the discussion of the results and conclusions appropriate and detailed?	{0.0, 0.5, 1.0}

After evaluating the 411 eligible works accordingly to the previously discussed QE criteria (the scores of each record are available in the GitHub repository), the first conclusion of the authors is that works with a non-detailed or not appropriate methodology, results' discussion, or conclusions should not be included in the review. Another conclusion is relative to rejecting works that do not consider either localization or mapping problems, or do not present any long-term experimental results, given the focus of this review on the long-term localization and mapping problem for mobile robots. Furthermore, the quality assessment phase should consider a cut-off score to filter works with low quality scores. Consequently, the assessment phase considers the following two reasons to reject a record:

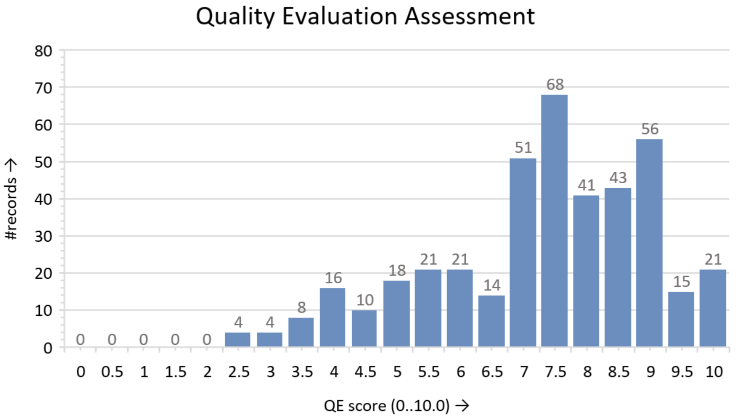
1. QE2, QE3, QE5, QE8: reject works with a 0.0 (no compliance) score;
2. cut-off score: reject works with a score lower or equal to 7.5/10.0.

The distribution of the evaluation scores and the QE criteria itself justify the selection of a 7.5/10.0 cut-off score. Figure 2 illustrates the scores distribution for all eligible works versus the scores of the ones that pass the first criterion defined previously for the QE phase (related to the compliance on the QE2, QE3, QE5, and QE8 criteria). The assessment of this criterion rejects 116 records (28%) of the 411 eligible works (see Figure 1). Even though the distribution of the evaluation scores changes significantly in the range of scores lower or equal to 7.5/10.0, as observed between Figures 2b and 2a, only one work with a score higher than 7.5 is rejected due to not having a detailed and appropriate discussion of the results. This result indicates that interesting works are associated with high scores, as intended when using a quality assessment methodology, while also suggests that the range between 8.0 and 10.0 have the most interesting and quality works compatible with the focus of this review on long-term localization and mapping. Although only assessing the eligible works would seem to lead to the same results in terms of records included in the review, the rejection criterion on QE2/3/5/8 prevents outliers related to the quality assessment. From the remaining 295 eligible works, cut-off scores from 7.5 up to 8.5 have the following corresponding rejection rates:

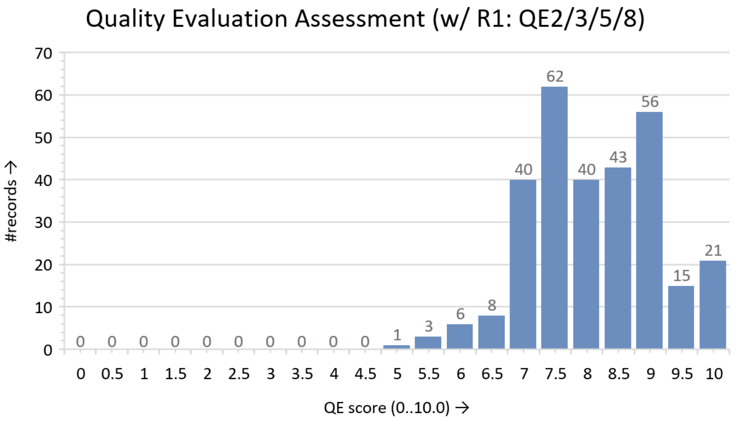
- 7.5/10.0   120 records (40.7%)   175 records
- 8.0/10.0 $\xrightarrow{\text{reject}}$ 160 records (54.2%) $\xrightarrow{\text{include}}$ 135 records
- 8.5/10.0   203 records (68.8%)   92 records

The 8.5 cut-off score would not be suitable because methods that focus only on localization or mapping, or not having either the implementation or the experimental data publicly available would be obligated to have maximum scores in the other criteria to be included in the review. In these cases, a work would have a maximum score of 9.0 due to partial compliance on QE3 or no compliance on the QE7 criteria. Likewise, a cut-off score of 8.0 would only leave a margin for having a single partial compliance on QE1, QE2, QE4 or QE8 criteria in similar cases, even though it would reject 160/295 (54%) records. Therefore, the 7.5/10.0 cut-off score is more appropriate for the quality assessment phase in this review by leaving margin for works to have partial compliance in more than one criterion. Indeed, this cut-off score allows an article with no public data and/or implementation (e.g., due to confidentiality agreements) to have up to four criteria with partial compliance, depending on the criterion's maximum score or if the work has available the experiments data and/or implementation. Another example is articles that only focus on localization or mapping. In these cases, the work could have no public implementation, even though requiring a maximum score on all other criteria, or, if the work has public data or implementation available, two other criteria could have partial compliance.

Overall, as illustrated in Figure 1, the quality assessment of the 411 eligible works considering the two rejection criteria previously mentioned leads to rejecting a total of 236 (57%) records. As a result, the remaining 175 records will be analyzed for data extraction.



(a)



(b)

Figure 2: Distribution of the quality evaluation scores obtained from assessing the eligible works considered in the review: (a) all eligible works; (b) works that pass the rejection criterion during the QE assessment related to QE2/3/5/8 = 0.0 (no compliance).

3.4 Data extraction

The data extraction process analyzes the records selected after the quality assessment phase and extracts information from these works. In the scope of this review, the Data Extraction (DE) items required for each record are the following ones:

- [**DE1**] **Long-term considerations** – long-term factors the works consider in their proposed approach and experiments. Considering the knowledge obtained in the previous phases of this review's methodology, the authors considered the following factors for categorizing the included works:
  - appearance: varying conditions, appearance changes;
  - dynamics: environment dynamics, dynamic elements;
  - sparsity: map pruning, redundant data removal;
  - multi-session: map management;
  - computational: memory management, efficiency.
- [**DE2**] **Localization** – how the robot localizes itself and the type of localizer;
- [**DE3**] **Mapping** – type of the map;
- [**DE4**] **Multi-robot** – if the proposed methodologies consider multi-robot systems;
- [**DE5**] **Execution mode** – offline, online, if requires both, or if no information on this item;
- [**DE6**] **Environment and domain** – type of environment (indoor, outdoor) and domains (air, ground, water) tested with the proposed methodologies;
- [**DE7**] **Sensory setup** – which sensors considered in the methodologies;
- [**DE8**] **Non-public experiments** – if the authors performed experiments or tests with non-public data;
- [**DE9**] **Ground-truth** – how ground-truth for non-public data is obtained or its type, if available;
- [**DE10**] **Distance and time characteristics** – relative to the non-public experiments if available, as follows:
  - total distance (km) of the non-public experiments;
  - path (km), in the case of repetitive paths;
  - total time (h) in terms of continuous operation;
  - time interval (day/week/month/year, or d/w/m/y) between the first and the last run.
- [**DE11**] **Datasets** – if and which public datasets are used in the experiments;
- [**DE12**] **Evaluation metrics** – which metrics are used for evaluation.

In Section 5, a comparison table of the public datasets identified by the DE11 will contain the sensory setup, ground-truth data availability from the datasets, and the distance and time characteristics, similar to the data extraction items for non-public data, among other aspects. As a result, the distinction between public and non-public data availability represented in DE8, DE9, and DE10 allows to understand the distance and time characteristics of non-public data independently from the public datasets.

Although the data extraction phase in a systematic literature review usually does not remove any records, 31 of the analyzed 179 works have extended versions of the proposed methodologies, more detailed ones, or equivalent methods applied in different conditions. Thus, these records are not included in the review to improve the discussion section in terms of singularity and originality of proposed approaches for the long-term localization and mapping problem. The extracted information helped identifying the corresponding extended and more complete versions of these works. A document containing the association of the removed versions to the records included in the review is available in the public GitHub repository, including their bibliographic references.

Consequently, 144 original works are included in this review for an overview of these records in Section 4, and their synthesis and discussion in Section 5. The information relative to the 12 data items for each of the included records is available in Appendix A and also in the repository. The included works represent 35% of the 411 eligible records for this review. This result indicates that the methodology followed in this review led to a high percentage of quality results.

4 Results Overview

In this section, the main goal is to overview the results not in terms of their scientific contribution but in terms of their bibliographic data for presenting an overview of the included records in the review. First, statistic results of the data sources in which the 144 included records could be identified in the methodology allow the evaluation of the coverage between the sources. Next, the tool VOSviewer (van Eck and Waltman 2010, 2014) is used to obtain the co-occurrence analysis for the keywords and the authors. The former focus on the keywords recency and their occurrence in the sources, while the latter discusses the research networks between the authors, and the ones with more publications in long-term localization and mapping. Lastly, two analysis are presented relative to the evolution of the publication year and most relevant publication venues.

4.1 Data source

The results on the identification phase are exported to BibTeX files from each data source. This exportation considers all the information available in the data sources, such as citation (e.g., author, title, publication venue, and type of record) and bibliographic (e.g., affiliation and the publisher) information of each record, the abstract, and author and indexed keywords. Next, using the `bibtexparser`[3] Python library, the BibTeX files are processed to identify uncompleted records. For example, the DOI must be specified and, if not available, the record's information must be manually completed with a corresponding URL. Then, considering the 144 included records in this review, a Python script searches each record in the BibTeX files corresponding to each data source. This search uses the DOI, URL, and title data to identify if a data source had in its identification results the searched record. Given that these three fields can contain lower and upper letters, the respective strings must be compared only after converting them to lower cases. As a result, the number of identified records by each data source of the 144 included ones in the review are the following ones:

- *ACM Digital Library*: 25 records (17.4%);
- *Dimensions*: 85 records (59.0%);
- *IEEE Xplore*: 68 records (47.2%);
- *INSPEC*: 104 records (72.2%);
- *Scopus*: 122 records (84.7%);
- *Web of Science*: 105 records (72.9%).

The database *Scopus* is the source that identified the greatest number of included records. This result was expected given that *Scopus* is considered as one of the largest curated databases (V. K. Singh et al. 2021), indexing more than 25000 active titles and 7000 publishers[4]. Two other sources with more than 70% of identified records are *INSPEC* and *Web of Science*. Similarly to *Scopus*, these two databases index also records from thousands of journals, conferences, and publishers[5,6]. Although *Dimensions* is also a bibliographic database covering millions of publications from thousands of sources, this database is the newest one (created in 2018) relative to the other three considered in this review (*INSPEC*, *Scopus*, and *Web of Science*) and could be a factor to why it obtained a lower percentage (59.0%) than the other three databases. Another possible reason is that *Scopus* and *Web of Science* have the majority of their coverage in Life Sciences, Physical Sciences, and Technology Area (including the Engineering subject area related to the topic of this review), while *Dimensions* has better coverage in Social Sciences and Arts & Humanities (V. K. Singh et al. 2021). Even though *IEEE Xplore* is a digital library and only indexes works published by IEEE and its partners, this data source returns 47.2% of the include records in the review. The main reason is that this library indexes publications related to electrical engineering and computer science, subject areas related to long-term localization and mapping[7]. Finally, the *ACM Digital Library* using *The ACM Guide to Computing Literature* collection only finds published records by ACM and possible links to other records focused exclusively on computing[8] and not directly related to the Computer Science or Engineering subject areas, explaining why this source obtained a lower coverage percentage of the included results than the other sources for this review.

Furthermore, Table 4 presents a coverage analysis of the identified results from each data source for the 144 included records in this review. Table 4a presents the pairwise overlap between sources. The corresponding percentage is the ratio of records identified by both sources to the one between the two that has the smallest number of results: $\#\{A \cap B\}/\min\{\#A, \#B\}$, where $\#A$ and $\#B$ is the number of results for a data source A and B, respectively, and $\#\{A \cap B\}$ is the intersection results between the two sources. For example, if the pairwise results is 100%, it means that the data source with more records found was capable of obtaining all the results, i.e., had full coverage over the other source. Table 4b reports the percentage of records identified by at least one of two data sources over all 144 included records: $\#\{A \cup B\}/144$, where $A \cup B$ is the union correspondence results of the sources A and B. This percentage represents the joint coverage of two databases over the 144 included records.

Table 4: Pairwise coverage analysis of the data sources considered in the review over the 144 included records: (a) identification only on both pairwise sources ($\#\{A \cap B\}/\min\{\#A, \#B\}$); (b) on either ones ($\#\{A \cup B\}/\#\text{records}$). Legend: dim – *Dimensions*, ieee – *IEEE Xplore*, insp – *INSPEC*, scop – *Scopus*, wos – *Web of Science*.

(a)

$A \cap B$	**acm**	**dim**	**ieee**	**insp**	**scop**	**wos**
acm	–	96.0%	44.0%	88.0%	96.0%	96.0%
dim	–	–	69.1%	77.6%	97.6%	95.3%
ieee	–	–	–	89.7%	91.2%	73.5%
insp	–	–	–	–	87.5%	68.3%
scop	–	–	–	–	–	89.5%
wos	–	–	–	–	–	–

(b)

$A \cup B$	**acm**	**dim**	**ieee**	**insp**	**scop**	**wos**
acm	–	59.7%	56.9%	74.3%	85.4%	73.6%
dim	–	–	73.6%	85.4%	86.1%	75.7%
ieee	–	–	–	77.1%	88.9%	85.4%
insp	–	–	–	–	93.8%	95.8%
scop	–	–	–	–	–	92.4%
wos	–	–	–	–	–	-

Analyzing the coverage results in Table 4, the first observation is that the pairwise union results of two sources increase the independent coverage of each source. This observation validates the need identified in the methodology discussed in Section 3 to consider several data sources in the identification phase of a review. Moreover, the pairwise union coverage of *INSPEC*, *Scopus*, and *Web of Science* is greater than 90% of the included records. When evaluating the joint coverage of these three databases, they identify all 144 of the included records, i.e., a 100% coverage. Although this result could indicate that those three sources guarantee full coverage of the long-term localization and mapping research topic, it is always advisable to consider as most as possible sources in the methodology. Another observation is relative to the overlap of *Scopus* with the other sources, which is greater than 85%. This overlap indicates that *Scopus* covers results not only on the topic of this review but also the results obtained by the other sources considered in the methodology. Lastly, *IN-*

[3]https://bibtexparser.readthedocs.io/en/master/
[4]https://www.elsevier.com/solutions/scopus/how-scopus-works
[5]https://www.elsevier.com/solutions/engineering-village/content/inspec
[6]https://clarivate.com/webofsciencegroup/solutions/web-of-science/
[7]https://ieeexplore.ieee.org/Xplorehelp/overview-of-ieee-xplore/about-ieee-xplore
[8]https://libraries.acm.org/digital-library/acm-guide-to-computing-literature

SPEC and *Web of Science* achieve a pairwise overlap percentage of 68.3% between themselves, while their union represents 95.8% of the included records. This discrepancy indicates that these two sources identify unique results between themselves. Indeed, *INSPEC* identifies 33/144 records not found by *Web of Science*, and vice-versa for *Web of Science*, with 34/144 unique records.

4.2 Keywords co-occurrence

Next, VOSviewer (van Eck and Waltman 2010, 2014) is used to analyze the co-occurrence of keywords in the included articles. This co-occurrence is the relatedness of items determined based on the number of documents in which the keywords occur together. For this analysis, first, a Python script processes the BibTeX file containing the citation and bibliographic information, the author and the indexed keywords, and the abstract of the records to join the author with the indexed keywords in the same `keywords` field. Then, an online tool[9] converts this processed BibTeX to a RIS file. Even though VOSviewer supports file types directly exported from *Dimensions*, *Scopus*, or *Web of Science* as input, none of these data sources obtained all the 144 included records of the review in the identification phase. Given that VOSviewer does not support BibTeX files, the conversion to RIS file is required for using as input. The disadvantage of using this file format in VOSviewer is only allowing to perform co-occurrence of items (e.g., keywords or authors), while bibliographic data from *Dimensions*, *Scopus*, or *Web of Science* in CSV files allow also other analysis such as citation, co-citation, or bibliographic coupling. However, the creation of these CSV files follow different templates depending on the data source. So, RIS files allow the integration of all 144 included records for obtaining the two co-occurrence analysis presented in this review (namely, keywords and co-authorship).

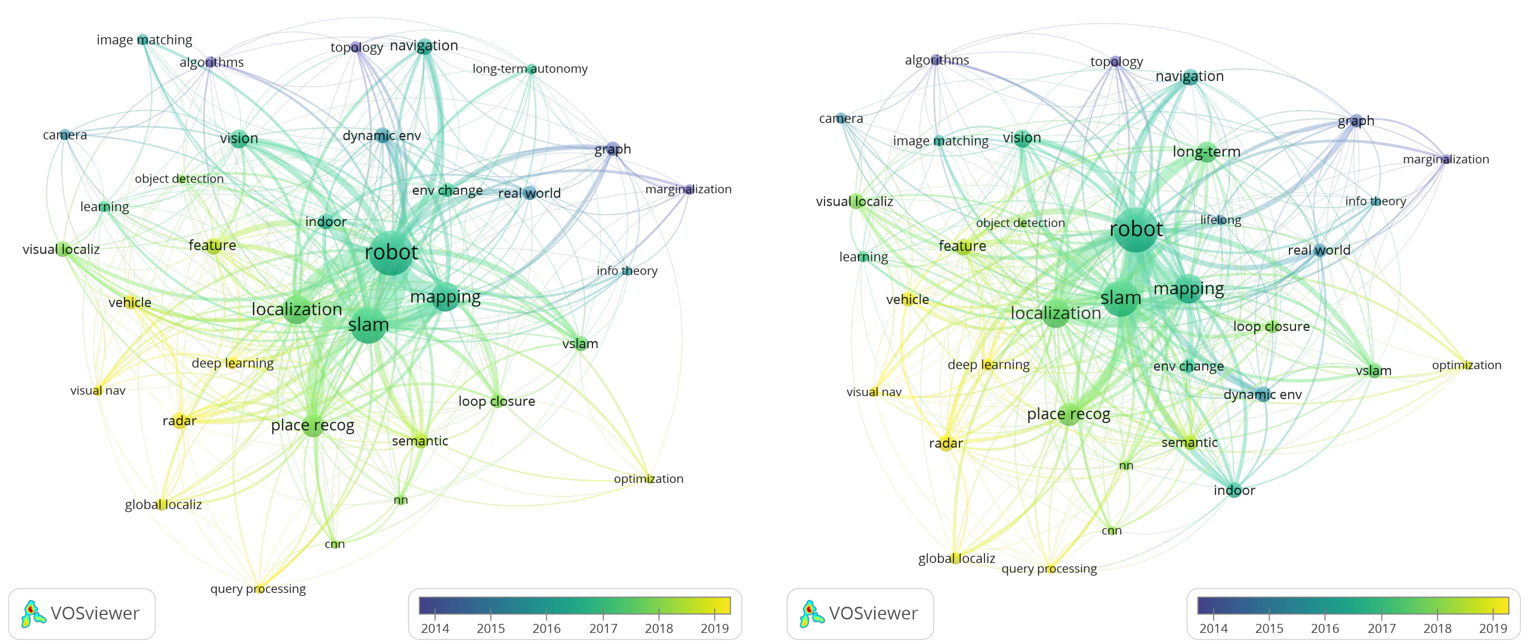
In Figure 3a, the network presents the overlay visualization of the keywords co-occurrence in the included records weighted by the number of occurrences of each term, using full counting for the links' strength. The latter computes the strength of the links directly by the number of co-occurrences of the respective two terms. The overlay visualization colors the keywords differently according to the average publication year of the included records in which each of the keywords appears. This coloring allows analyzing which are the ones that are associated with the most recent publications. As for the keywords' weighting, the number of occurrences dictates the size of the circles. Furthermore, the minimum number of occurrences of a keywords set in VOSviewer for obtaining the graph is 5 originating the 35 keywords illustrated in Figure 3a. This parameter was selected for visualization purposes while also filtering uninteresting keywords. Similarly, setting the attraction and repulsion parameters to 2 and 0, respectively, distances the terms more from each other than using the values recommended in the VOSviewer manual[10] (2 and 1, respectively). These two parameters only interfere in the localization of the terms in the map, not in the graph connections. Lastly, a thesaurus of the keywords (available in the repository) is used to join similar terms: spelling differences (e.g., localization – localisation), full terms versus abbreviations (simultaneous localization and mapping – SLAM), while also allowing the concatenation of long keywords for visualization reasons.

Overall, the keyword `robot` is the one that appears more times in the included records: 111 occurrences, links with 34 other terms, and has a total link strength of 403 (sum of co-occurrences of all of its links). This result expectable due to the relation of this review's topic to robotics. Similarly, three other keywords in the network related to long-term localization and mapping topic with high values of occurrence, number of links, and total link strength are `slam` (75, 34, and 288), `mapping` (48, 33, and 204), and `localization` (47, 32, and 194, respectively). The methodology for the search strategy discussed in Section 3.2 considers all of these four keywords. Thus, the significant influence of `robot`, `slam`, `mapping`, and `localization` in the keywords co-occurrence analysis indicates that, after the all the phases executed in this review's methodology, the 144 included records have a high correlation with the keywords considered in the search query. Given that the keywords are usually selected or indexed to capture the essence of the document, this correlation indicates that the search query is appropriate to obtain the search results, even considering only the keywords as search fields.

As for keywords related to the outcome of the PICO framework, `long-term autonomy` occurs only 6 times in the included records, linking with 16 other keywords and having a total link strength of 27. This low occurrence could indicate that the term `long-term autonomy` is not usually used by the authors nor indexed by the databases. However, the specific term of `long-term autonomy` does not summarize all the possibilities for the outcome of the PICO framework (see Section 2). Indeed, for this reason, the search query for the identification phase uses only the following single terms: `"long term"` and `"life long"` (resumes the possibility of having a space or a hyphen), and `lifelong`. Figure 3b presents the keywords co-occurrence analysis using the same parameters for obtaining Figure 3a. The difference to the latter network is using a thesaurus that summarizes all the keywords that contain `long-term` and `lifelong` into the terms themselves, obtaining 36 keywords with a minimum of 5 occurrences in the 144 included records. In terms of occurrences, number of links, and total link strength, the impact of the thesaurus keyword `long-term` is 25, 28, and 105, and for lifelong 6, 17, and 31, respectively. These values are much higher than the ones respective only to `long-term autonomy` from Figure 3a. The reason is that `long-term` in Figure 3b compiles the occurrences of keywords such as `long-term autonomy`, `long-term mapping`, and `long-term localization` (6, 2, and 2 occurrences, respectively), and `lifelong` sum up, for example, three different versions of `lifelong learning` (using `lifelong`, `life-long` and `life long` with 2, 1, and 2 occurrences, respectively) and `lifelong slam` (1 occurrence). Hence, these results proves that the third `AND` part of the search query (`"long term" OR "life long" OR lifelong`) covers well the PICO framework's outcome. Plus, they also show no consensus among the authors and by the databases indexation on how to define a keyword for the topic of long-term localization and mapping.

In terms of the average year of publication, analyzing the diagrams in Figure 3 on its colorization, the first observation is the recency of terms related to visual localization. The keywords visual SLAM (`vslam`), visual navigation (`visual nav`), and visual localization (`visual localiz`) have all an average publication year higher than 2017. This recency indicates that recent approaches related to the topic of this review, long-term localization and mapping, are more inclined to use vision as a sensorization input. Another sensor that appeared with high relevance in the network is `radar`, with 15 occurrences and an average publication year of 2019.20. This sensor is agnostic to the environment changes such as illumination and season changes intrinsically associated with vision and could be why the recent works related to

[9]https://www.bibtex.com/c/bibtex-to-ris-converter/
[10]https://www.vosviewer.com/documentation/Manual_VOSviewer_1.6.8.pdf



(a) (b)

Figure 3: Keywords co-occurrence analysis on the 144 included records generated by VOSviewer with overlay visualization by the average publication year: (a) original keywords; (b) all keywords containing long-term and lifelong summarized by the terms themselves. Parameters used for generating the co-occurrence network: minimum number of occurrences = 5, attraction = 2, repulsion = 0, scale = 1.49, circles size variation = 0.5, lines size validation = 1.0. Legend: `cnn` – Convolutional Neural Networks, `env` – environment, `localiz` – localization, `nav` – navigation, `nn` – Neural Networks, `recog` – recognition, `vslam` – visual SLAM.

long-term localization and mapping are using it. Moreover, place recognition (`place recog`) stands out not only by its recency but importance. The keyword itself (`place recog`) occurs 31 times and an average publication year of 2017.77, with terms related to place recognition such as `loop closure` and global localization (`global localiz`) with high average publication years (2017.82 and 2018.75, respectively) and strong link to place recognition (5 co-occurrences for each of the links between `loop closure` and `global localiz` with `place recog`). Lastly, machine learning also seems to be used in recent works included in this review. The keywork learning occurs 7 times with an average publication year of 2017.00. Neural Netowrks (`nn`), Convolutional Neural Networks (`cnn`), and `deep learning` have a similar number of occurrences (6, 5, and 8) and publication years higher than 2017 (2017.83, 2018.00, and 2019.12, respectively). These results could mean another trend of using machine learning to improve the long-term autonomy of mobile robots.

Although the recency of keywords related to dynamic environments is lower than 2017 (2015.50 and 2016.75 for `dynamic env` and `env change`), they have a high occurrence (14 and 12, respectively), located close to each other in the network, and have a strong link between them (4 co-occurrences). Three keywords also located near each other are `graph`, `marginalization`, and information theory (`info theory`) while having similar average publication years (2014.36, 2014.00, and 2015.50, respectively). Even though the number of occurrences of these terms is low (11, 6, and 5 for `graph`, `marginalization`, and `info theory`, respectively), their map proximity could indicate a focus in the past on the topic of graph sparsity, i.e., maintaining the graph in the long-term to only depend on the environment size and not on the robot's operation time. However, all of these tendencies indicated in this keywords co-occurrence analysis among other ones will be discussed in Section 5 in further detail.

4.3 Co-authorship analysis

The other analysis obtained using VOSviewer is the co-authorship network presented in Figure 4. Similar to the keywords network illustrated in Figure 3, the co-occurrence of the authors' names creates links among them in the graph. The strength of these links is dictated by the number of documents the two authors of a link are co-authors in the same record, and the number of co-authored works determines the size of the circles respective to each author in the graph. In contrast to Figure 3, the network in Figure 4 does not have any overlay specific to coloring depending on the average publication year. Instead, the main goal of the co-authorship analysis in this review is to present possible research networks detected in the 144 included records. Thus, the coloring in Figure 4 represents the clusters of authors detected by VOSviewer. This network only considers authors with a minimum of 3 works for relevance and visualization reasons, resulting in 29 authors. Also, authors identified only by the initial of the first name and by the surname can lead to incorrect correspondences in terms of co-authorship. Indeed, VOSviewer detects 392 authors in the 144 included records using the original RIS file used in Section 4.2 compared to 413 after checking the authors names. Hence, a manual check is performed on all authors of the included records to guarantee no false correspondences for the co-authorship analysis with VOSviewer. This manual check ensures each author has its full first and surname and any middle initials while also using the same name for an author in different records.

Analyzing Figure 4, the co-authorship network presents 8 clusters. These clusters are separated from each other, i.e., no link exists between authors from different clusters. However, this separation does not mean that there is not any co-authorship between authors from different clusters only indicating that for a miminum of 3 co-authored documents there is not a connection between these 8 clusters. Even so, the graph presented in Figure 4

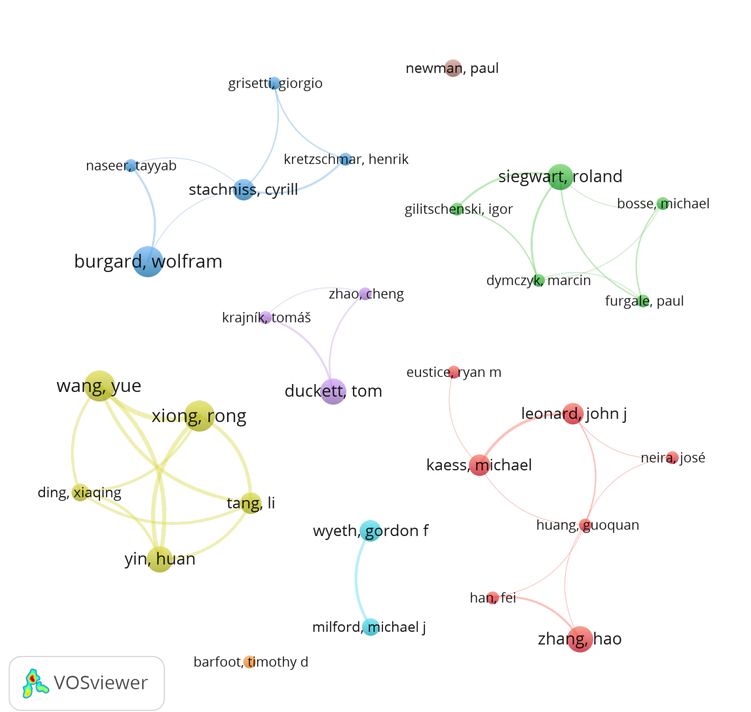


Figure 4: Co-authorship analysis on the 144 included records generated by VOSviewer. Parameters used for generating the co-occurrence network: minimum number of occurrences = 3, attraction = 2, repulsion = -3, scale = 1.49, circles size variation = 1.0, lines size validation = 1.0.

allows the identification of the most relevant research networks in terms of number of co-authored documents and in the context of long-term localization and mapping, considering the 144 records included in this review. As a results, the following enumeration presents the authors that belong to each cluster in the format of author (number of co-authored documents):

1. Rong Xiong (7), Yue Wang (7), Huan Yin (6), Li Tang (5), and Xiaqing Ding (4);
2. Hao Zhang (6), John J. Leonard (5), Michael Kaess (5), Fei Han (3), Guoquan Huang (3), José Neira (3), and Ryan M. Eustice (3);
3. Wolfram Burgard (7), Cyrill Stachniss (5), Giorgio Grisetti (3), Henrik Kretzschmar (3), and Tayyab Naseer (3);
4. Roland Siegwart (6), Igor Gilitschenski (3), Marcin Dymczyk (3), Michael Bosse (3), and Paul Furgale (3);
5. Tom Duckett (6), Cheng Zhao (3), and Tomáš Krajník (3);
6. Gordon F. Wyeth (5) and Michael J. Milford (4);
7. Paul Newman (4);
8. Timothy D. Barfoot (3).

When analyzing the affiliations of the authors mentioned previously at the time of publication, all authors of the first cluster belonged to the State Key Laboratory of Industrial Control and Technology (SKLICT) and the Institute of Cyber-Systems and Control at Zhejiang University in China. Even though Huan Yin, Yue Wang, Xiaqing Ding, Li Tang, and Rong Xiong mention their affiliation to the Joint Centre for Robotics Research between Zhejiang University, China, and the University of Technology Sydney, Sydney, in the work (H. Yin, Y. Wang, et al. 2020), this affiliation only appeared in this article. The total link strength (sum of all links weights) of each of the authors in that cluster is higher than 16, meaning a high co-authorship between them. Indeed, all five authors have links between all of them. Similar to the first cluster, the third, fourth, fifth, and sixth clusters have common affiliations within each one: the Autonomous Intelligent Systems at the University of Freiburg in Germany, the Autonomous Systems Lab (ASL) at ETH Zürich in Switzerland, the Lincoln Centre for Autonomous Systems (LCAS) at the University of Lincoln in UK, and the School of Electrical Engineering and Computer Science at Queensland University of Technology (QUT) in Australia. However, the interlinking between the authors is not as strong as in the first cluster, as shown in Figure 4 by the authors of these clusters not being connected between all the ones within each cluster. Even so, the common affiliation shows there is considerable interest by these research units in the long-term localization and mapping topic.

The affiliation analysis in the second cluster is more complex given that there was no affiliation common to all authors at the time of the records' publication. Instead, the following affiliations were found: Fei Han and Hao Zhang with the Department of Computer Science at Colorado School of Mines in the USA, Guoquan Huang with the Department of Mechanical Engineering at the University of Delaware in the USA, John J. Leonard and Michael Kaess with the Computer Science and Artificial Intelligence Laboratory (CSAIL) at the Massachusetts Institute of Technology (MIT) in the USA, Ryan M. Eustice with the Perceptual Robotics Laboratory (PeRL) at the University of Michigan in the USA, and José Neira with the Instituto Universitario de Investigación en Ingeniería de Aragón (I3A) at the Universidad de Zaragoza in Spain. Although there are 5 different affiliations to which the 7 authors stated in the respective records, 4 of the research institutions noted for the second cluster are in the USA, indicating a possible reason for facilitating the linkage between these authors from different research units.

In terms of the clusters composed by single authors, the affiliations of Paul Newman and Timothy D. Barfoot are the Oxford Robotics Institute at the University of Oxford in UK and the Autonomous Space Robotics Laboratory (ASRL) at the University of Toronto Institute for Aerospace Studies (UTIAS) in Canada, respectively. Even though these two authors are not linked with any others in the network, the co-authorship analysis indicates that they have an interest in long-term localization and mapping. This interest is shown by their number of co-authored records: 4 and 3 by Paul Newman and Timothy D. Barfoot, respectively.

As for the number of co-authored publications, considering the 144 included records, the authors that appeared to have more research on the review's topic are Rong Xiong, Yue Wang, and Wolfram Burgard, given the 7 co-authored publications of each one. However, Rong Xiong and Yue Wang have co-authored the 7 documents attributed to each of them. This relation and similar ones can biase the analysis of which authors are having more impact in the review's topic. The clustering shown in Figure 4 allows a more unbiased analysis relative to the co-authorship links between authors. Thus, based on the clustering, the most influential authors in long-term localization and mapping are the following ones: Rong Xiong (or Yue Wang), Hao Zhang, Wolfram Burgard, Roland Siegwart, Tom Duckett, Gordon F. Wyeth, Paul Newman, and Timothy D. Barfoot.

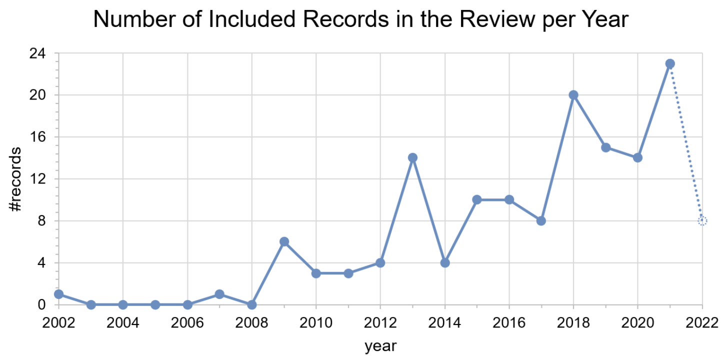


Figure 5: Evolution of published records per year considering the 144 included records in this review

4.4 Year of publication

The relevance of the long-term localization and mapping topic can be evaluated by the evolution of the number of publications. Figure 5 presents this evolution from the earliest year of publication of the included records to the year at the time of writing this article. The latter has its respective data dashed to indicate that the last year is not completed at the time of writing. Analyzing Figure 5, this review's topic seems to have gain relevance in 2009 with 6 works, compared to only one publication in 2007 and another in 2002 in the previous years to 2009. From that year onwards, the graph has a linear tendency reaching a maximum of 23 records in 2021, while already having 8 publications in 2022 until May 17, 2022. This tendency shows that long-term localization and mapping is gaining interest throughout the years and, consequently, supports the importance and relevance of this review for the scientific community.

4.5 Publication venue

Finally, the last overview of the 144 included records in the review is relative to the publication venue. Table 5 presents the venues with more than 1 publication, separating the journals and conferences in two different tables (Tables 5a and 5b, respectively). The columns μ present the average year of publication of the records associated to a certain venue, while max columns display the publishing recency by the year of the most recent publication in the venue. For comparing to the average value (μ), the third column (σ) of each table presents the standard deviation based on the publication year data. The last column state the number of records published in the venue from the 144 records included in the review for discussion.

In terms of journals, the Robotics and Autonomous Systems, IEEE Robotics and Automation Letters, and the International Journal of Robotics stand out with more than 10 publications. Also, these journals have a high standard deviation (greater than 1.5), indicating that the publications spread out throughout the years. In the case of the IEEE Robotics and Automation Letters, these results gain more relevance indicating a recent trend on publishing on this journal, considering that its creation was only on 2015[11]. With more than 5 publications, the Journal of Field Robotics and the Autonomous Robots have recent average of publication (2017) with a high standard deviation (greater than 2.0), similarly indicating that authors have been publishing in these two journals along the years. In contrast, the IEEE Transactions on Intelligent Transportation Systems and Sensors journals have a standard deviation lower than 1 year, with an average publication year of at least 2019. The recency of publication on these two journals with a very low deviation suggests a recent interest of the authors to publish in these two journals works related to long-term localization and mapping.

[11] https://www.ieee-ras.org/publications/ra-l

Table 5: Publication venues of the included records in this review with more than one record published in the venue: (a) journals; (b) conferences. Legend: μ – average year of publication, σ – standard deviation of the publication year, max – maximum year of publication, # – number of records published at a certain venue

(a)

	Year			
Journal	μ	σ	max	#
Robotics and Autonomous Systems	2016	3.9	2021	13
IEEE Robotics and Automation Letters	2019	1.7	2022	12
International Journal of Robotics Research	2014	3.2	2022	11
Journal of Field Robotics	2017	3.5	2022	8
Autonomous Robots	2017	2.2	2020	7
IEEE Transactions on Intelligent Transportation Systems	2021	0.8	2022	4
Sensors	2019	0.8	2020	4
IEEE Transactions on Robotics	2017	3.1	2022	4
IEEE Sensors Journal	2020	1.5	2021	2
International Journal of Advanced Robotic Systems	2020	1.5	2021	2

(b)

	Year			
Conference	μ	σ	max	#
IEEE International Conference on Robotics and Automation (ICRA)	2016	3.9	2021	22
IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)	2017	3.8	2021	18
IEEE International Conference on Robotics and Biomimetics (ROBIO)	2019	2.1	2021	3
IEEE International Intelligent Transportation Systems Conference (ITSC)	2018	2.4	2021	3
European Conference on Mobile Robots (ECMR)	2014	0.9	2015	3
IEEE Intelligent Vehicles Symposium (IV)	2019	0.5	2019	2
International Conference on 3D Vision (3DV)	2018	1.5	2019	2
International Conference on Advanced Robotics (ICAR)	2011	2.0	2013	2

As for conferences, the data in Table 5b shows a high discrepancy in the number of publications related to this review's topic in ICRA and IROS compared to the other venues. Indeed, all the other conferences have only a maximum of 3 records published in them, compared to 22 and 18 papers in ICRA and IROS, respectively. When considering that 62 of the 144 included records are published in conferences, ICRA and IROS with a total of 40 published works related to this review's topic represent 65% of works published in conferences and 27.8% of all included records. This result expresses the high relevance of ICRA and IROS in the topic of long-term localization and mapping.

5 Discussion

5.1 Appearance variance

5.2 Dynamic environments

5.3 Map sparsification

5.4 Multi-session

5.5 Computational

5.6 Evaluation metrics

5.7 Long-term experimental data

Table 6: Datasets used in the 144 included records for long-term localization and / or mapping experiments. Legend: odo – odometry (wheeled, laser, visual, inertial, or a combination of odometry sources, dist. – total distance length of the dataset, path – total path distance if repeated several times, time – total operation time, int. – time interval between the start and end acquisition dates / time instants (d/m/y equivalent to day/month/year, 0 if only 1 run), and seq. – number of sequences of the dataset.

				Sensor														Calib.								
					camera							laser														
Dataset	**Long-term**	**Environ.**	**Domain**	**odo**	**gray**	**color**	**monocular**	**stereo**	**omni**	**RGBD**	**thermal**	**2D**	**3D**	**radar**	**sonar**	**IMU**	**GPS**	**intrinsic**	**extrinsic**	**GT data**	**Format**	**dist. (km)**	**path (km)**	**time (h)**	**int. (d/m/y)**	**#seq.**
St Lucia Brisbane 2007	dynamic, lighting variance	outdoor (urban)	ground (car)		x		x													–	–	66	–	1.67	–	1
Intel Research Lab 2003	map maintenance	indoor (office)	ground (robot)	x								x								–	CARMEN	0.506	–	0.75	–	1
FHW	map maintenance	indoor (museum)	ground (TOURBOT)	x								x								–	CARMEN	–	–	1.98	–	1
FR079	map maintenance	indoor (office)	ground (robot)	x								x								–	CARMEN	–	–	0.29	–	1
FR101	map maintenance	indoor (office)	ground (robot)	x								x								–	CARMEN	–	–	0.29	–	1
New College	dynamic, lighting variance	outdoor (campus)	ground (Segway)	x	x	x		x	x			x				x	x	x	x	GPS	plain text (non-image), png (stereo), jpg (omni)	2.2	–	0.73	–	1
TUM RGBD	dynamic, lighting variance	indoor (office, industrial hall)	ground (hand-held, Pioneer 3)			x				x						x		x	x	motion capture system (MotionAnalysis)	plain text (non-image), png (image + depth)	0.285	–	0.35	–	15
COLD	dynamic, lighting variance, weather variance	indoor (office)	ground (Pioneer 3, ATRV Mini, PeopleBot)	x		x	x		x			x								laser-based localization, manual corrections	plain text (non-image), jpg (image)	0.92	–	0.99	–	76
Bicocca (indoor)	dynamic, lighting variance	indoor (office)	ground (Robocom)	x	x	x	x	x	x			x			x	x		x	x	floorplans, visual tags, multiple lasers-based localization	plain text (non-image), png (image)	–	–	2.5	3d	5
New College (FAB-MAP)	dynamic, lighting variance, viewpoint variance	outdoor (campus)	ground (robot)			x	x										x	x		image correspondence, GPS	plain text (non-image), jpg (image)	1.9	–	–	–	1
City Center (FAB-MAP)	dynamic, lighting variance, viewpoint variance	outdoor (urban)	ground (robot)			x	x										x	x		image correspondence matrix, GPS	plain text (non-image), jpg (image)	2	–	–	–	1
MIT Killian Court	map maintenance	indoor (office)	ground (robot)	x								x			x					–	CARMEN	–	–	2.13	–	1
albert-b-laser-vision	map maintenance, lighting variance	indoor (office)	ground (iRobot B21r)	x		x	x					x								–	CARMEN (non-image), jpg (image)	–	–	0.18	–	1
CoBots long-term	map maintenance, dynamic, lighting variance, seasonal variance	indoor (office)	ground (robot)	x		x				x		x								–	ROS bag	131	–	260	2y3m	1082
MIT Stata Center	map maintenance, dynamic, lighting variance, seasonal variance	indoor (office)	ground (PR2)	x		x		x		x		x				x				floorplans	ROS bag	42	–	38	1y9m	84
KITTI	dynamic, lighting variance	outdoor (urban)	ground (car)		x	x	x	x					x			x	x	x	x	RTK GPS/INS	png (image), binary (laser), plain text (imu, gps)	–	–	1.18	8d	61
CMU-VL	dynamic, lighting variance, seasonal variance	outdoor (urban)	ground (car)			x	x										x	x	x	GPS	–	–	8.5	–	1y	16
Oxford RobotCar	dynamic, lighting variance, seasonal variance, weather variance	outdoor (urban)	ground (car)	x		x	x	x				x	x			x	x	x	x	RTK GPS/INS	png (image), binary (laser), plain text (imu, gps, odo)	1010.46	10	–	1y8m	133
CMU-Seasons	dynamic, lighting variance, seasonal variance	outdoor (urban)	ground (car)			x	x											x	x	image correspondence	jpg (image)	–	8.5	–	330d	17
RobotCar Seasons	dynamic, lighting variance, seasonal variance, weather variance	outdoor (urban)	ground (car)			x	x	x										x	x	image correspondence	jpg (image)	–	10	–	178d	10
Nordland	lighting variance, seasonal variance, weather variance	outdoor (railway)	ground (train)			x	x										x			GPS	mp4 (video stream), plain text (gps)	2916	729	39.74	–	4
Malaga 2009	dynamic, lighting variance	outdoor (parking, campus)	ground (car)			x	x					x				x	x	x	x	RTK GPS/INS	Rawlog MRPT	6.358	–	–	–	6

Table 6: continued from previous page

				Sensor														Calib.								
					camera							laser														
Dataset	**Long-term**	**Environ.**	**Domain**	**odo**	**gray**	**color**	**monocular**	**stereo**	**omni**	**RGBD**	**thermal**	**2D**	**3D**	**radar**	**sonar**	**IMU**	**GPS**	**intrinsic**	**extrinsic**	**GT data**	**Format**	**dist. (km)**	**path (km)**	**time (h)**	**int. (d/m/y)**	**#seq.**
Ford Campus	dynamic, lighting variance	outdoor (campus, urban)	ground (car)			x			x			x	x			x	x	x	x	RTK GPS/INS	LCM log	–	–	–	2m	–
NCLT	dynamic, lighting variance, seasonal variance, weather variance	indoor, outdoor (campus)	ground (Segway)			x			x			x	x			x	x	x	x	RTK GPS/INS + "large" SLAM	binary (laser), tiff (image), plain text (non-laser or image)	147.4	–	34.9	1y4m	27
Gardens Point Campus of QUT	dynamic, lighting variance	indoor, outdoor (campus)	ground (handheld)			x	x													ground-plane position	png (images), plain text (ground plane)	–	–	–	–	3
Witham Wharf RGB-D (LCAS STRANDS)	dynamic, lighting variance, seasonal variance	indoor (office)	ground (SCITOS-G5)			x				x		x								–	ROS bag	–	–	–	1y1m	368
EuRoC	lighting variance	indoor (industrial hall, office)	air (AscTec Firefly)		x		x	x								x		x	x	motion capture system (Vicon), 3D position + structure scan (Leica MS50)	ROS bag	0.8936	–	0.37	–	11
UTIAS Multi-Robot	lighting variance, viewpoint variance	indoor (empty space)	ground (iRobot Create)	x		x	x											x		motion capture system (Vicon)	jpg (image), dat (non-image)	–	–	4.78	–	9
Alderley Brisbane	dynamic, lighting variance	outdoor (urban)	ground (car)			x	x													manual frame tagging (longitude, latitude)	–	16	8	–	–	2
Freiburg Across Seasons	dynamic, lighting variance, seasonal variance	outdoor (urban)	ground (car)			x		x									x			GPS, manual corrections	jpg (image)	110	–	–	3y	3
Berlin Kudamm	dynamic, lighting variance, viewpoint variance	outdoor (urban)	ground (car)			x	x													image correspondence	jpg (image)	–	–	–	–	2
MulRan	dynamic	outdoor (urban)	ground (car)										x	x		x	x		x	full SLAM (w/ RTK-GPS)	binary (laser), CSV (global pose, radar ray), png (radar polar image)	41.2	–	–	2m15d	12
YQ21	dynamic, lighting variance	outdoor (campus)	ground (car)			x	x	x					x			x	x	x	x	RTK-GPS	binary (laser), jpg (images), plain text (gps)	–	–	–	7d	21
CBD	dynamic, lighting variance, viewpoint variance	outdoor (urban)	ground			x	x	x												image correspondence	png (images)	–	–	–	–	1
USyd Campus	dynamic, lighting variance, seasonal variance	outdoor (campus)	ground (car)	x		x	x						x			x	x	x	x	GPS	ROS bag	–	–	–	1y	52
Lip6Indoor	viewpoint variance	indoor (office)	ground (handheld)			x	x											x		image correspondence	ppm (images)	–	–	6m28s	–	1
Lip6Outdoor	dynamic, lighting variance	outdoor (campus)	ground (handheld)			x	x											x		image correspondence	ppm (images)	–	–	17m42s	–	1
KAIST	dynamic, lighting variance	outdoor (urban)	ground (car)			x		x			x					x	x	x		RTK-GPS	png (images), plain text (imu, gps)	84	–	–	18d	36
Bonn RGB-D Dynamic	dynamic	indoor (office)	ground			x				x								x		motion capture system (OptiTrack), structure scan (Leica BLK360)	png (images, depth), plain text (imu, gps)	–	–	–	–	26
IPLT	dynamic, lighting variance, seasonal variance, weather variance	outdoor (parking)	ground (car)	x	x		x					x					x	x	x	GPS	ROS bag	–	0.2	–	2y	127
RADIATE	dynamic, lighting variance, weather variance	outdoor (parking, urban)	ground (car)			x	x	x					x	x		x	x	x	x	RTK-GPS	ROS bag	–	–	4.98	–	–
NTU VIRAL	lighting variance	indoor, outdoor (campus)	air (DJI M600)		x		x	x					x			x		x	x	motion capture system (Leica MS60)	ROS bag	1.845	–	0.9	–	9

Table 6: continued from previous page

				Sensor														Calib.								
					camera							laser														
Dataset	**Long-term**	**Environ.**	**Domain**	**odo**	**gray**	**color**	**monocular**	**stereo**	**omni**	**RGBD**	**thermal**	**2D**	**3D**	**radar**	**sonar**	**IMU**	**GPS**	**intrinsic**	**extrinsic**	**GT data**	**Format**	**dist.** (km)	**path** (km)	**time** (h)	**int.** (d/m/y)	**#seq.**
Oxford Radar RobotCar	dynamic, lighting variance, weather variance	outdoor (urban)	ground (car)	x		x	x	x					x	x		x	x	x	x	RTK-GPS, optimized VO + loop + GPS/INS	png (image, raw laser, radar), binary (laser), plain text (imu, gps, odo)	280	10	–	1m	32

5.8 Final observations

6 Challenges and Future Directions

7 Limitations of the Study

Section to discuss possible limitations of the study (timeframe, wider approach, etc.).

- only one query for discussion: e.g., for searching datasets, possibly, a different query should have been used
- overview long-term SLAM vs in-depth analysis and discussion of each type of techniques: our review synthesizes all types of techniques, if the reader wants an in-depth analysis, different reviews should be performed
- limited information on the experiments conditions (traveled distance, duration, etc.) given by the authors

8 Conclusions

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A Data Extraction Results of the Included Records in the Systematic Literature Review on Long-Term Localization and Mapping for Mobile Robots

Table 7: Data extraction items retrieved from the included records in the review

DE:	1:					2:	3:	4:	5:		6:					7:	8:	9:	10:				11:	12:
Ref.	appearance	dynamic	sparsity	multi-session	computational	localization	mapping	multi-robot	offline	online	indoor	outdoor	air	ground	water	sensor	exp. self-acq.	ground-truth	dist. (km)	path (km)	time (h)	int. (d/m/y)	datasets	metrics
Davison and Murray 2002			x			EKF (2D, 3DoF)	feature (Harris corner detector)	–		x	x			x		wheel odometry, camera (gray, stereo)	x	manual	–	–	–	–	–	innovation covariance, pose error
Filliat 2007	x					image classification (location)	dictionary (BoW, location category)	–	x	x	x			x		camera (color, mono)	x	manual	–	–	–	1d	–	confusion matrix, localization rate
Konolige and Bowman 2009	x		x			visual odometry (3D, 6DoF), vocabulary tree (location)	keyframe (graph, 6DoF edges)	–		x	x			x		camera (stereo)	x	–	–	–	–	4d	–	execution time, localization rate, memory
Bosse and Zlot 2009	x				x	point cloud matching (2D, 3DoF)	submap (2D point cloud, graph, 3DoF edges)	–		x		x		x		laser (2D)	x	SLAM-based	245.9	–	6.8	5d	–	pose error, ROC curves
Biber and Duckett 2009		x				point cloud matching (2D, 3DoF)	submap (2D point cloud, graph, 3DoF edges)	–	x	x	x			x		wheel odometry, laser (2D)	x	–	9.6	–	–	5w	–	average point cloud likelihood, covariance eigenvalues, memory
Hochdorfer and Schlegel 2009			x			EKF (2D, 3DoF)	feature (SURF)	–		x	x			x		wheel odometry, camera (omni)	x	position	0.115	–	–	–	–	position error, #map points
Hochdorfer, Lutz, et al. 2009			x			EKF (2D, 3DoF)	feature (SURF)	–		x	x			x		wheel odometry, camera (omni)	x	position	0.15	–	–	–	–	covariance eigenvalues, position error, #map points
Nuske et al. 2009	x					particle filter (2D, 3DoF)	feature (building edges)	–		x		x		x		wheel odometry, camera (mono)	x	laser-based	3.92	–	10.5	1d	–	execution time, localization rate, pose error
Glover et al. 2010	x					visual odometry (2D, 3DoF), Bayesian (location)	experience (graph, pose + local views, 3DoF edges)	–	x	x		x		x		camera (mono)	–	–	–	–	–	–	St Lucia 2007	confusion matrix, precision-recall, #nodes
Kretzschmar, Grisetti, et al. 2010			x			point cloud matching (2D, 3DoF)	pose graph (graph, 2D point clouds, 3DoF edges)	–		x	x			x		laser (2D)	–	–	–	–	–	–	FR079, Intel 2003	execution time, graph connectivity, #edges, #nodes
Ikeda and Kanji 2010					x	particle filter (location)	dictionary (semantic hashing)	–	x	x		x		x		camera (mono)	x	GPS	40	20	–	–	–	execution time, localization rate, memory
Dayoub et al. 2011		x				feature matching (location)	keyframe (graph, 6DoF edges)	–		x	x			x		camera (omni)	x	initial position, laser-based	–	–	–	3d	–	orientation error, similarity score
Kretzschmar, Stachniss, and Grisetti 2011			x			point cloud matching (2D, 3DoF)	pose graph (graph, 2D point clouds, 3DoF edges)	–		x	x			x		laser (2D)	–	no pruning	–	–	–	–	FR079, Intel 2003	#edges, #nodes
Pirker et al. 2011			x			feature matching (3D, 6DoF)	keyframe (graph)	–		x	x	x		x		camera (gray, mono)	x	–	1.2	–	–	2w	–	position error, #map points
Walcott-Bryant et al. 2012		x	x			point cloud matching (2D, 3DoF)	pose graph (graph, 2D point clouds, 3DoF edges)	–		x	x			x		laser (2D)	x	–	8.4	–	–	5w	–	execution time, position error, #edges, #nodes
Kretzschmar and Stachniss 2012			x			point cloud matching (2D, 3DoF)	pose graph (graph, 2D point clouds, 3DoF edges)	–		x	x			x		laser (2D)	–	–	–	–	–	–	FHW, FR079, FR101, Intel 2003	execution time, #edges, #nodes
Maddern, Milford, et al. 2012			x			wheel odometry (2D, 3DoF), particle filter (location)	pose graph (graph, 3DoF edges)	–		x		x		x		wheel odometry, camera (color, mono)	–	–	–	–	–	–	New College (FAB-MAP)	execution time, memory, precision-recall
Latif, Cadena, et al. 2012				x		–	pose graph (graph)	–		x	x	x		x		odometry	–	–	–	–	–	–	Bicocca (indoor), Intel 2003, New College	ATE, execution time
Kawewong et al. 2013	x					vocabulary tree (location)	dictionary (BoW, hierarchical tree)	–		x	x	x		x		camera	–	–	–	–	–	–	City Center (FAB-MAP), New College (FAB-MAP)	execution time, precision-recall
Bacca et al. 2013		x	x			Bayesian (2D, 3DoF)	keyframe (graph)	–		x	x			x		camera (omni), laser (2D)	x	no pruning	1.635	–	–	1y	–	pose error, precision-recall, #map points
Ball et al. 2013	x					visual odometry (2D, 3DoF), feature matching (location)	experience (graph, pose + local views, 3DoF edges)	–		x		x		x		camera (mono)	–	–	–	–	–	–	New College, St Lucia 2007	pose error, #nodes
Einhorn and Gross 2013		x	x			odometry	pose graph (graph, 2D/3D NDT)	–		x	x			x		camera (mono, RGBD), laser (2D)	x	–	7	–	3	2d	–	execution time, #nodes
Tipaldi et al. 2013		x				particle filter (2D, 3DoF)	grid (occupancy, 2D)	–	x	x	x			x		laser (2D)	x	manual, SLAM-based	–	–	–	1d	–	computational complexity, localization rate, pose error
Huang et al. 2013			x			odometry, point cloud matching (2D, 3DoF)	pose graph (graph, 2D point clouds, 3DoF edges)	–		x	x			x		wheel odometry, laser (2D)	x	simulation	–	–	–	–	Intel 2003, MIT Kilian Court	pose error, #nodes
Johannsson et al. 2013			x			odometry (3D, 6DoF), BoW (location)	keyframe (graph, 6DoF edges)	–		x	x			x		wheel odometry, camera (stereo, RGBD), IMU	–	manual, no pruning	–	–	–	–	MIT Stata Center	execution time, #localization failures, #nodes
Oberländer et al. 2013				x	x	Fourier-Mellin transform matching (2D, 3DoF)	submap (2D occupancy grid, graph, 3DoF edges)	–		x	x			x		wheel odometry, laser (2D)	–	SLAM-based	–	–	–	–	albert-b-laser-vision, FR079, Intel 2003	execution time, pose error, precision-recall
Saarinen et al. 2013		x				–	3D NDT, grid (occupancy, 3D)	–		x	x			x		camera (RGBD), laser (3D)	x	–	5	–	17	–	TUM RGBD	execution time, map similarity
Biswas and Veloso 2013b	x					particle filter (2D, 3DoF)	feature (2D line segments)	–		x	x			x		wheel odometry, camera (RGBD), laser (2D)	–	manual	–	–	–	–	CoBots	pose error, #localization failures
Paul and Newman 2013			x			image classification (location)	database (images, semantic visual topics)	–	x	x		x		x		camera (color, mono)	x	GPS, manual	28	–	–	–	City Center (FAB-MAP), New College (FAB-MAP)	execution time, f-beta, precision-recall
V. A. Nguyen et al. 2013	x					feature matching (location)	pose graph (graph)	–		x	x			x		camera (color, mono)	–	–	–	–	–	–	COLD	computational complexity, execution time, localization rate
Maddern, Milford, et al. 2013			x			particle filter (2D, 3DoF)	pose graph (graph, 3DoF edges)	–		x		x		x		wheel odometry, camera (color, mono)	–	manual	–	–	–	–	New College	execution time, memory, pose error, precision-recall

Table 7: continued from previous page

DE:	1:					2:	3:	4:	5:		6:					7:	8:	9:	10:				11:	12:
Ref.	**appearance**	**dynamic**	**sparsity**	**multi-session**	**computational**	**localization**	**mapping**	**multi-robot**	**offline**	**online**	**indoor**	**outdoor**	**air**	**ground**	**water**	**sensor**	**exp. self-acq.**	**ground-truth**	**dist. (km)**	**path (km)**	**time (h)**	**int. (d/m/y)**	**datasets**	**metrics**
Churchill and Newman 2013	x					visual odometry (3D, 6DoF)	experience (graph, local views, observability edges)	–		x	x			x		camera (color, stereo)	x	RTK-GPS	37	0.7	–	3m	–	execution time, #localization failures
Pomerleau et al. 2014		x				point cloud matching (3D, 3DoF)	point cloud (laser, 3D)	–		x		x		x		wheel odometry, laser (3D)	x	map, targeted speed	3.9	1.3	–	7m	–	execution time, velocity error
Murphy and Sibley 2014	x		x			image classification (location)	keyframe (graph)	–		x		x		x		camera (color, mono)	x	–	–	–	–	1w	New College	execution time, confusion matrix, precision-recall, #nodes
Carlevaris-Bianco, Kaess, et al. 2014			x			odometry, point cloud matching (2/3D, 3/6DoF)	pose graph (graph)	–		x	x	x		x	x	camera (mono), laser (2D/3D)	–	no pruning	–	–	–	–	Intel 2003, MIT Kilian Court, NCLT	execution time, KLD, #nodes
Williams et al. 2014					x	odometry (3D, 6DoF)	pose graph (graph)	–		x		x	x	x		wheel odometry, camera (color, stereo), IMU	x	RTK-GPS, simulation	–	–	–	–	KITTI	execution time, KLD
Einhorn and Gross 2015		x	x			odometry	pose graph (graph, 2D/3D NDT)	–		x	x			x		camera (mono, RGBD), laser (2D)	x	–	7	–	3	2d	–	execution time, #nodes
Pérez et al. 2015	x					particle filter (3D, 6DoF)	pose graph (graph, 6DoF edges)	–	x	x		x		x		wheel odometry, camera (gray, stereo), laser (2D)	x	SLAM-based	11.5	–	3.5	–	–	pose error
Li et al. 2015	x			x		feature matching (location)	pose graph (graph)	–	–	–		x			x	camera (gray, mono)	x	manual	–	–	–	3y	–	confusion matrix
Mohan et al. 2015					x	BoW (location)	dictionary (BoW)	–	x	x		x		x		camera (color, mono)	–	–	–	–	–	–	Bicocca (indoor), Ford Campus, Malaga 2009, New College, Nordlandsbanen, St Lucia 2007	confusion matrix, execution time, precision-recall
Dymczyk, Lynen, et al. 2015			x			feature matching (location)	keyframe (graph)	–	x	x		x		x		camera (mono)	x	no pruning	1.034	–	–	10d	–	f-score, localization rate, #nodes
Rapp et al. 2015		x				particle filter (2D, 3DoF)	grid (occupancy, 2D)	–	–	–		x		x		odometry, radar	x	–	–	–	–	–	–	pose error
Vysotska et al. 2015	x					image sequence matching (location)	database (images, sequence)	–	–	–		x		x		camera (color, mono)	x	manual	3	–	–	–	–	computational complexity, confusion matrix, precision-recall
Neubert et al. 2015	x					feature matching (location)	dictionary (translation, winter - summer)	–	–	–		x		x		camera (color, mono)	–	–	–	–	–	–	Nordlandsbanen	precision-recall
Mur-Artal et al. 2015			x			bundle adjustment (3D, 6DoF)	keyframe (graph)	–		x		x		x		camera (gray, mono)	–	–	–	–	–	–	KITTI, New College, TUM RGBD	ATE, execution time, pose error, recall, #nodes
Naseer, Suger, et al. 2015	x					image sequence matching (location)	–	–	x			x		x		camera (color, mono)	x	GPS	–	–	–	–	New College (FAB-MAP)	f-beta, precision-recall
Karaoğuz and Bozma 2016	x					feature matching (location)	pose graph (graph, similarity edges)	–		x	x	x		x		camera (color, mono)	x	–	0.325	–	–	–	COLD, New College	execution time, precision-recall
Santos et al. 2016		x				–	grid (occupancy, 3D)	–		x	x			x		camera (RGBD)	x	simulation	–	–	–	5d	–	environment model error, execution time
Dymczyk, Stumm, et al. 2016	x					feature matching (location)	–	–		x	x	x		x		camera (gray, mono), IMU	x	feature labels	4.05	0.15	–	3m	NCLT	execution time, f-score
Dymczyk, Schneider, et al. 2016			x			–	keyframe (graph)	–		x	x			x		camera, IMU	x	SLAM-based	–	0.15	–	–	–	f-score, #map points
Gadd and Newman 2016	x		x			visual odometry (3D, 6DoF)	experience (graph, local views, 6DoF edges)	x		x		x		x		camera (grey, mono)	x	–	100	–	–	1m	–	memory, #localization failures
Mazuran et al. 2016			x			–	pose graph (graph)	–		x	x			x		–	–	–	–	–	–	–	Intel 2003, MIT Kilian Court	KLD, #nodes
Ozog et al. 2016			x	x		particle filter (3D, 6DoF)	pose graph (graph, planar segments, 6DoF edges)	–		x		x			x	camera (gray, mono), IMU, DVL	x	map model	10.159	–	–	3y	–	KLD, pose error, #nodes
Mühlfellner et al. 2016			x	x		reprojection minimization (3D, 6DoF)	keyframe (graph)	–	x	x		x		x		wheel odometry, camera (gray, mono)	x	RTK-GPS	22	–	–	1y	–	computational complexity, localization rate, pose error, #map points
An et al. 2016	x	x				EKF (2D, 3DoF)	pose graph (graph)	–		x	x			x		wheel odometry, camera (gray, mono)	x	manual, simulation	0.254	–	0.33	–	–	pose error, #edges, #nodes
Taisho and Kanji 2016	x					image classification (location)	database (images, image features)	–	–	–		x		x		camera (color, mono)	x	manual	–	–	–	–	–	localization rate
Han, X. Yang, et al. 2017	x					feature matching (location)	–	–	x	x		x		x		camera (color, mono)	–	–	–	–	–	–	CMU-VL, Nordlandsbanen, St Lucia 2007	execution time, precision-recall
Biswas and Veloso 2017		x				Bayesian (2D, 3DoF)	feature (2D line segments)	–		x	x	x		x		wheel odometry, laser (2D), camera (RGBD)	–	manual, SLAM-based	–	–	–	–	CoBots	pose error, #localization failures
Griffith and Pradalier 2017	x		x	x		SIFT flow (3D, 6DoF)	pose graph (graph, 6DoF edges)	–	x			x			x	camera (color, mono), GPS, IMU	x	manual	100	–	–	1y2m	–	absolute alignment error
Naseer, Oliveira, et al. 2017	x				x	feature matching (location)	–	–		x		x		x		camera (color, mono)	x	manual	100	–	–	3y	–	f-score, precision-recall
Krajník, Fentanes, Santos, et al. 2017		x				–	grid (occupancy, 3D)	–		x	x	x		x		camera (RGBD)	x	external tracking system	–	–	–	112d	NCLT, Witham Wharf RGB-D	computational complexity, memory, pose error
Ila et al. 2017			x			odometry (3D, 6DoF)	pose graph (graph)	–		x	x	x		x		–	–	simulation	–	–	–	–	KITTI	pose error, #nodes
Latif, Huang, et al. 2017	x				x	dictionary search (location)	dictionary (incremental)	–		x		x		x		camera (mono)	–	–	–	–	–	–	Bicocca (indoor), KITTI, New College	confusion matrix, execution time, precision-recall
Xin et al. 2017	x					feature matching (location)	–	–	–	–		x		x		camera (mono)	–	–	–	–	–	–	CMU-VL, Gardens Point Campus	computational complexity, f-score, precision-recall
Bescos et al. 2018		x				bundle adjustment (3D, 6DoF)	keyframe (graph)	–	x		x			x		camera (color, mono, stereo, RGBD)	–	–	–	–	–	–	KITTI, TUM RGBD	ATE, execution time, pose error
Opdenbosch et al. 2018			x		x	–	keyframe (graph, Hamming distance edges)	–	–	–	x	x	x			camera (mono, stereo, RGBD)	–	–	–	–	–	–	EuRoC	memory
Han, H. Wang, et al. 2018	x					image sequence matching (location)	–	–	–	–		x		x		camera (color, mono)	–	–	–	–	–	–	CMU-VL, Nordlandsbanen, St Lucia 2007	precision-recall
Han, Beleidy, et al. 2018	x					feature matching (location)	–	–	–	–		x		x		camera (color, mono)	–	–	–	–	–	–	CMU-VL, Nordlandsbanen	precision-recall

Table 7: continued from previous page

DE:	1:					2:	3:	4:	5:		6:					7:	8:	9:	10:				11:	12:
Ref.	appearance	dynamic	sparsity	multi-session	computational	**localization**	**mapping**	multi-robot	offline	online	indoor	outdoor	air	ground	water	**sensor**	exp. self-acq.	**ground-truth**	dist. (km)	path (km)	time (h)	int. (d/m/y)	**datasets**	**metrics**
F. Cao, Zhuang, et al. 2018	x					odometry (3D, 6DoF), vocabulary tree (location)	pose graph (graph, 2D point clouds, 3DoF edges)	–		x		x		x		wheel odometry, laser (2D, 3D), IMU	x	–	–	–	–	1d	–	execution time, precision-recall
Nobre et al. 2018	x					Mahalanobis distance minimization (2D, 3DoF)	feature	–		x	x			x		wheel odometry, camera (color, mono)	x	simulation	–	–	–	–	UTIAS Multi-Robot	precision-recall
Hui Zhang et al. 2018			x			feature matching (3D, 6DoF)	keyframe (graph)	x		x	x	x		x		camera (mono)	x	–	–	–	–	–	KITTI	localization rate
J. Zhu et al. 2018	x				x	image sequence matching (location)	–	–	x			x		x		camera (color, mono)	–	–	–	–	–	–	City Center (FAB-MAP), Nordlandsbanen	precision-recall
MacTavish et al. 2018	x					visual odometry (3D, 6DoF)	keyframe (graph)	–		x		x		x		camera (stereo)	x	external tracking system	26.08	0.16	–	4m	–	execution time, localization rate, pose covariance, pose error
L. Sun et al. 2018		x				point cloud matching (3D, 6DoF)	grid (occupancy, 3D)	–	x	x		x		x		laser (3D)	x	manual	–	–	–	2w	KITTI	map accuracy
Lázaro et al. 2018		x	x	x		point cloud matching (2D, 3DoF)	submap (2D point cloud, graph, 3DoF edges)	–		x	x			x		wheel odometry, laser (2D)	–	–	–	–	–	–	MIT Stata Center, Witham Wharf RGB-D	execution time, #edges, #nodes
N. Zhang et al. 2018	x				x	visual odometry (3D, 6DoF)	keyframe (graph)	–		x		x		x		camera (stereo)	x	–	25	0.25	–	4m	–	matching accuracy
Chebrolu et al. 2018	x			x		feature matching (location)	–	–	–	–		x	x			camera (color, mono), GPS	x	manual	–	–	–	1m	–	matching accuracy
P. Yin, L. Xu, et al. 2018	x				x	feature matching (location)	grid (occupancy, 3D)	–	–	–		x		x		laser (3D)	–	–	–	–	–	–	KITTI, NCLT	precision-recall
Egger et al. 2018	x		x			feature matching (3D, 6DoF), odometry (3D, 6DoF)	submap (surfel, graph)	–		x		x		x		wheel odometry, laser (3D), IMU	x	RTK-GPS	–	–	–	1y6m	–	execution time, memory
Arroyo et al. 2018	x				x	image sequence matching (location)	–	–	–	–		x		x		camera (mono, stereo)	–	–	–	–	–	–	KITTI, New College, Nordlandsbanen	confusion matrix, execution time, precision-recall
Ouerghi et al. 2018	x					image sequence matching (location), visual odometry (3D, 2DoF)	keyframe (graph)	–		x		x		x		wheel odometry, camera (mono)	–	–	–	–	–	–	KITTI	execution time, pose error
Siva and Hao Zhang 2018	x					feature matching (location)	–	–	–	–		x		x		camera (omni)	x	GPS	19.15	–	–	1y	–	precision-recall
Luthardt et al. 2018	x		x			visual odometry (3D, 6DoF)	pose graph (graph)	–	x	x		x		x		camera (gray, mono)	x	GPS	–	–	–	–	–	pose error
Chen, L. Liu, et al. 2018	x					image classification (location)	–	–	–	–		x		x		camera (color, mono)	–	–	–	–	–	–	Nordlandsbanen, St Lucia 2007	precision-recall
Yu et al. 2019	x					vocabulary hashing (location)	–	–	–	–		x		x		camera (color, mono)	–	–	–	–	–	–	City Center (FAB-MAP), New College (FAB-MAP)	confusion matrix, precision-recall
Boniardi et al. 2019		x	x			point cloud matching (2D, 3DoF)	pose graph (graph, 2D point clouds, 3DoF edges)	–		x	x			x		laser (2D)	x	external tracking system, map model	4.657	–	2.85	4d	–	execution time, pose error, #nodes
G. Kim, B. Park, et al. 2019	x					feature matching (location)	grid (location, 2D)	–	–	–		x		x		laser (3D)	–	–	–	–	–	–	NCLT, Oxford RobotCar	precision-recall
Berrio, Ward, et al. 2019	x		x			point cloud matching (2D, 3DoF)	feature (pole, corners)	–	x			x		x		laser (3D)	x	manual	–	–	–	6m	–	pose covariance, #map points
K. Wang et al. 2019		x				bundle adjustment (3D, 6DoF)	keyframe (graph)	–	–	–	x	x		x		camera (RGBD)	x	simulation	–	–	–	–	TUM RGBD	ATE, precision
L. Wu and Y. Wu 2019					x	image classification (location)	–	–		x		x		x		camera (color, mono)	–	–	–	–	–	–	Gardens Point Campus, Nordlandsbanen	execution time, f-score, precision-recall
Tang, Y. Wang, Ding, et al. 2019	x		x			BoW (location), point cloud matching (3D, 6DoF)	submap (graph, manifold)	–		x		x		x		camera (color, stereo)	–	SLAM-based	–	–	–	–	YQ21	execution time, localization rate, pose error, #nodes
Bürki et al. 2019	x			x		feature matching (3D, 6DoF)	keyframe (graph)	–	x	x		x		x		wheel odometry, sensor (gray, mono)	x	–	–	–	–	1y	NCLT	execution time, pose error
Labbé and Michaud 2019				x	x	BoW (location), odometry (2/3D, 3/6DoF)	pose graph (graph)	–		x	x	x	x	x		wheel odometry, camera (stereo, RGBD), laser (2D/3D)	–	–	–	–	–	–	EuRoC, KITTI, MIT Stata Center, TUM RGBD	ATE, execution time, #nodes
M. Zhang et al. 2019		x				point cloud matching (2D, 3DoF)	grid (occupancy, 2D)	–		x	x			x		laser (2D)	x	SLAM-based	–	–	–	–	–	execution time, pose error
Schmuck and Chli 2019			x			odometry (3D, 6DoF)	keyframe (graph)	–		x	x		x			camera, IMU	–	–	–	–	–	–	EuRoC	pose error
Ganti and Waslander 2019		x				bundle adjustment (3D, 6DoF)	keyframe (graph)	–	–	–		x		x		camera (stereo)	–	–	–	–	–	–	KITTI	pose error
Ding, Y. Wang, Tang, et al. 2019			x		x	EKF (3D, 6DoF)	keyframe (graph)	–		x		x		x		camera (stereo), IMU	x	laser-based	–	–	1.32	1y	–	ATE, communication constraints
Song et al. 2019		x				odometry (3D, 6DoF)	keyframe (graph)	–		x		x		x		camera, IMU	x	RTK-GPS	–	–	–	–	–	pose error
Pan et al. 2019		x				odometry, reprojection minimization (3D, 6DoF)	feature (point clusters)	–	x	x		x		x		camera (mono), laser (3D)	x	–	–	–	–	3m	KITTI	execution time, localization rate, pose error, reprojection error
A. J. B. Ali et al. 2020					x	visual odometry (3D, 6DoF)	keyframe (graph)	–		x	x			x		camera (RGBD)	x	laser-based	–	–	0.5	–	TUM RGBD	communication constraints, execution time, localization rate, memory, pose error
C. Qin et al. 2020	x					feature matching (location)	–	–		x		x		x		camera (color, mono)	–	–	–	–	–	–	Alderley, FAS, Nordlandsbanen, Oxford RobotCar, St Lucia 2007	confusion matrix, execution time, precision-recall
Martini et al. 2020	x					feature matching (location), point cloud matching (2D, 3DoF)	experience (graph)	–	x	x		x		x		radar	–	–	–	–	–	–	Oxford Radar RobotCar	confusion matrix, localization rate, pose error, precision-recall
Karaoğuz and Bozma 2020			x			–	pose graph (graph)	x		x		x		x		camera (mono)	x	–	–	–	–	–	COLD	computational complexity, precision-recall

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Ref.	appearance	dynamic	sparsity	multi-session	computational	**localization**	**mapping**	multi-robot	offline	online	indoor	outdoor	air	ground	water	**sensor**	exp. self-acq.	**ground-truth**	dist. (km)	path (km)	time (h)	int. (d/m/y)	**datasets**	**metrics**
H. Yin, Y. Wang, et al. 2020	x				x	particle filter (2D, 3DoF), point cloud matching (3D, 6DoF)	pose graph (graph, 6DoF edges)	–		x		x		x		laser (3D)	–	–	–	–	–	–	KITTI, YQ21	execution time, f-score, pose error, precision-recall
Clement et al. 2020	x					feature matching (3D, 6DoF)	–	–	–	–		x		x		camera (color, mono)	–	–	–	–	–	–	Oxford RobotCar	confusion matrix, matching accuracy
L. Wang et al. 2020		x				particle filter (2D, 3DoF)	grid (occupancy, 2D)	–		x	x			x		wheel odometry, laser (2D)	x	simulation, SLAM-based	–	–	–	–	–	execution time, memory, pose error
Camara et al. 2020	x				x	feature matching (location)	–	–		x		x		x		camera	–	–	–	–	–	–	Berlin Kudamm, Gardens Point Campus, Nordlandsbanen	execution time, memory, precision-recall
Gao and Hao Zhang 2020	x					feature matching (location)	–	–	–	–		x		x		camera (color, mono)	–	–	–	–	–	–	CMU-VL, St Lucia 2007	precision-recall
S. Yang et al. 2020		x				visual odometry (3D, 6DoF)	keyframe (graph)	–		x	x			x		camera (RGBD)	–	–	–	–	–	–	TUM RGBD	ATE, execution time, pose error
Siva, Nahman, et al. 2020	x					feature matching (location)	–	–	–	–		x		x		laser (3D)	x	simulation	–	–	–	–	NCLT	precision-recall
T. Qin et al. 2020	x					EKF (2D, 3DoF)	feature (semantic)	–		x	x	x		x		wheel odometry, camera (color, mono), IMU	x	RTK-GPS	0.324	–	–	1m	–	ATE, memory, recall
Ding, Y. Wang, Xiong, et al. 2020	x	x		x		bundle adjustment (3D, 6DoF)	point cloud (3D)	–	x	x		x		x		camera (color, stereo), laser (3D)	–	–	–	–	–	–	KITTI, YQ21	ATE, execution time, pose error
Yue et al. 2020		x				–	point cloud (3D)	x		x		x		x		camera (color, mono, thermal), laser (3D)	x	–	–	–	–	–	–	ATE, memory
Schaefer et al. 2021	x		x			particle filter (2D, 3DoF)	feature (poles)	–	x	x		x		x		laser (3D)	–	–	–	–	–	–	KITTI, NCLT	pose error
B. Liu et al. 2021	x					EKF (3D, 6DoF), feature matching (location)	keyframe (graph)	–		x	x	x		x		camera (color, mono), IMU	–	–	–	–	–	–	City Center (FAB-MAP), KITTI, New College (FAB-MAP)	execution time, memory, precision-recall
C. Kim et al. 2021					x	particle filter, point cloud matching (3D, 6DoF)	grid (geodetic, NDT)	–		x		x		x		laser (3D)	x	RTK-GPS, SLAM-based	–	–	–	–	KITTI	memory, pose error
Derner et al. 2021	x					feature matching (3D, 6DoF)	database (images, features, pose)	–	x	x	x			x		wheel odometry, camera (RGBD)	x	manual	0.198	–	–	–	Witham Wharf RGB-D	execution time, localization rate, pose error
F. Cao, Yan, et al. 2021	x					sequence matching (location)	–	–		x		x		x		laser (2D/3D)	–	–	–	–	–	–	NCLT, Oxford RobotCar	execution time, precision-recall
G. Singh et al. 2021	x	x				feature matching (location)	pose graph (graph, BoW)	–		x		x		x		camera (stereo, RGBD)	–	–	–	–	–	–	CBD, KITTI	execution time, precision-recall
Kurz et al. 2021			x			–	pose graph (graph)	–		x	x			x		wheel odometry, laser (2D), IMU	–	no pruning	–	–	–	–	MIT Stata Center, Witham Wharf RGB-D	execution time, pose error, #nodes
H. Yin, X. Xu, et al. 2021	x					location matching (location)	–	–	–	–		x		x		laser (3D), radar	–	–	–	–	–	–	MulRan, Oxford Radar RobotCar	confusion matrix, precision-recall
Thomas et al. 2021		x				point cloud matching (3D, 6DoF)	grid (occupancy, 3D)	–	x	x	x			x		wheel odometry, laser (3D)	x	simulation	–	–	–	–	–	confusion matrix, execution time, precision-recall
Berrio, Worrall, et al. 2021	x					–	grid (feature, 2D)	–	–	–		x		x		wheel odometry, camera (color, mono), laser (3D), IMU	–	–	–	–	–	–	USyd Campus	pose covariance
Oh and Eoh 2021	x					feature matching (location)	–	–	–	–		x		x		camera (color, mono)	–	–	–	–	–	–	KAIST, Nordlandsbanen	precision-recall
Tsintotas et al. 2021			x			BoW (location)	dictionary (BoTW, incremental)	–		x	x	x	x	x		camera (mono)	–	–	–	–	–	–	City Center (FAB-MAP), EuRoC, KITTI, Lip6Indoor, Lip6Outdoor, Malaga 2009	execution time, memory, precision-recall
Li Sun et al. 2021	x					feature matching (3D, 6DoF)	keyframe (graph)	–		x		x		x		camera (color, mono)	x	SLAM-based	0.741	–	–	1d	–	ATE, execution time, matching error, pose error
Tang, Y. Wang, Tan, et al. 2021	x					feature matching (location)	–	–	–	–		x		x		camera (color, mono)	–	–	–	–	–	–	Alderley, Nordlandsbanen, Oxford RobotCar, YQ21	localization rate, precision-recall
Piasco et al. 2021	x					feature matching (location)	–	–	x	x		x		x		camera (RGBD)	–	–	–	–	–	–	CMU-VL, Oxford RobotCar	precision-recall
P. Yin, J. Xu, et al. 2021	x					feature matching, sequence matching (location)	–	–		x		x		x		laser (3D)	x	–	132	11	–	–	KITTI, NCLT	execution time, memory, precision-recall
Meng et al. 2021	x					laser odometry (3D, 6DoF)	pose graph (graph)	–		x		x		x		laser (3D)	–	–	–	–	–	–	KITTI	ATE, execution time, pose error
S. Zhu et al. 2021		x				particle filter (2D, 3DoF)	grid (occupancy, 2D)	–	x	x	x			x		wheel odometry, camera (color, mono), laser (2D), IMU	x	manual	–	–	–	–	–	pose error
Zeng and Si 2021			x			–	pose graph (graph)	–		x	x			x		wheel odometry, camera (color, mono)	x	no pruning	–	–	–	–	–	#edges, #nodes
W. Ali et al. 2021			x		x	point cloud matching, visual odometry (3D, 6DoF)	keyframe (graph), submap (image, graph)	–		x	x	x		x		camera, laser (3D)	x	–	–	–	–	–	KITTI	CPU usage, memory, pose error, precision-recall
X. Xu et al. 2021	x					feature matching (location)	–	–		x		x		x		laser (3D)	–	–	–	–	–	–	MulRan, NCLT, Oxford RobotCar	execution time, precision-recall
Z. Yang et al. 2021	x				x	BoW, feature matching (location)	–	–		x		x		x		camera (color, mono)	–	–	–	–	–	–	City Center (FAB-MAP), KITTI, Lip6Indoor, Lip6Outdoor, Malaga 2009, New College	confusion matrix, execution time, precision-recall
Z. Wang et al. 2021	x		x			point cloud matching (3D, 6DoF)	feature (poles)	–	–	–		x		x		laser (3D)	x	GPS	5.52	–	–	1m	–	localization rate, pose error
Hu et al. 2022	x					feature matching (location)	–	–	–	–		x		x		camera (color, mono)	x	RTK-GPS	–	–	–	–	CMU-Seasons, RobotCar Seasons	execution time, precision-recall
Coulin et al. 2022	x					EKF (3D, 6DoF)	magnetic (vector)	–	x	x	x			x		camera (stereo), IMU	x	SLAM-based	1.665	–	–	1y	–	ATE, execution time
K. Zhang et al. 2022	x					feature matching (location)	–	–		x		x		x		camera (color, mono)	–	manual	–	–	–	–	City Center (FAB-MAP), KITTI, Malaga 2009, St Lucia 2007	execution time, precision-recall

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Ref.	**appearance**	**dynamic**	**sparsity**	**multi-session**	**computational**	**localization**	**mapping**	**multi-robot**	**offline**	**online**	**indoor**	**outdoor**	**air**	**ground**	**water**	**sensor**	**exp. self-acq.**	**ground-truth**	**dist.** (km)	**path** (km)	**time** (h)	**int.** (d/m/y)	**datasets**	**metrics**
T.-M. Nguyen, M. Cao, et al. 2022	x					bundle adjustment, sensor fusion (3D, 6DoF)	–	–		x	x		x			camera (mono), laser (3D), IMU, UWB	–	–	–	–	–	–	EuRoC, NTU VIRAL	execution time, pose error
Bouaziz et al. 2022			x	x		feature matching (3D, 6DoF)	keyframe (graph)	–	x	x		x		x		camera (gray, mono)	–	–	–	–	–	–	IPLT, Oxford RobotCar	execution time, memory, #localization failures
Du et al. 2022		x				reprojection minimization (3D, 6DoF)	keyframe (graph)	–		x	x			x		camera (RGBD)	–	–	–	–	–	–	Bonn RGB-D Dynamic, TUM RGBD	ATE, execution time, pose error
Xing et al. 2022		x				feature matching (3D, 6DoF)	keyframe (graph)	–		x	x	x	x	x		camera (RGBD), IMU	x	–	–	–	–	–	EuRoC, KITTI, TUM RGBD	execution time, localization rate, pose error
Hong et al. 2022	x					feature matching (location), point cloud matching (2D, 3DoF)	keyframe (graph)	–		x		x		x		radar	–	–	–	–	–	–	MulRan, Oxford RobotCar, RADIATE	ATE, execution time, pose error