

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;

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- 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 repository¹.

¹<https://github.com/sousararb/slrlthm-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 according 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 Reports², 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.

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

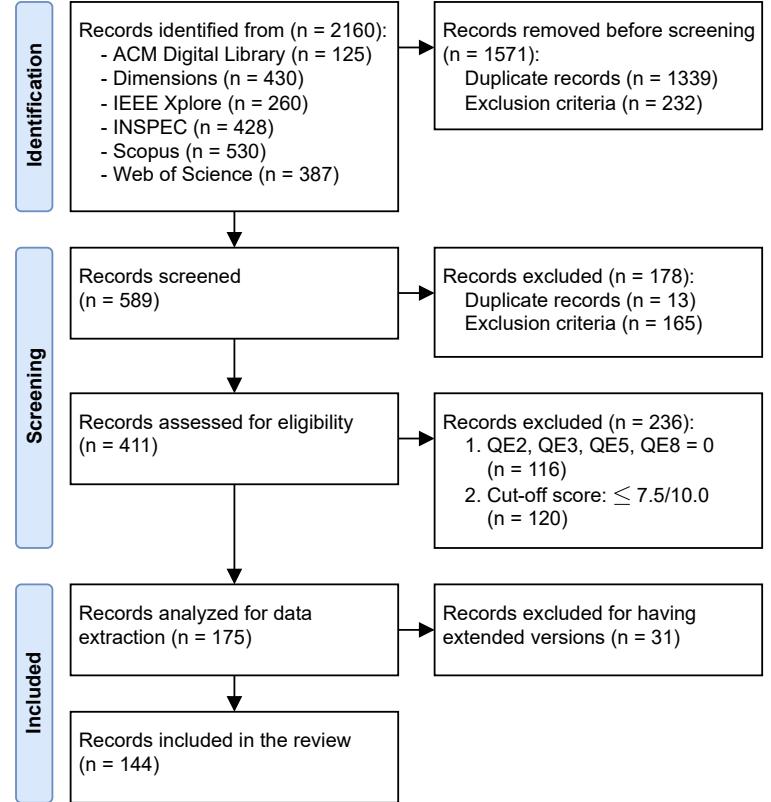


Figure 1: PRISMA flow diagram for the selection process.

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.

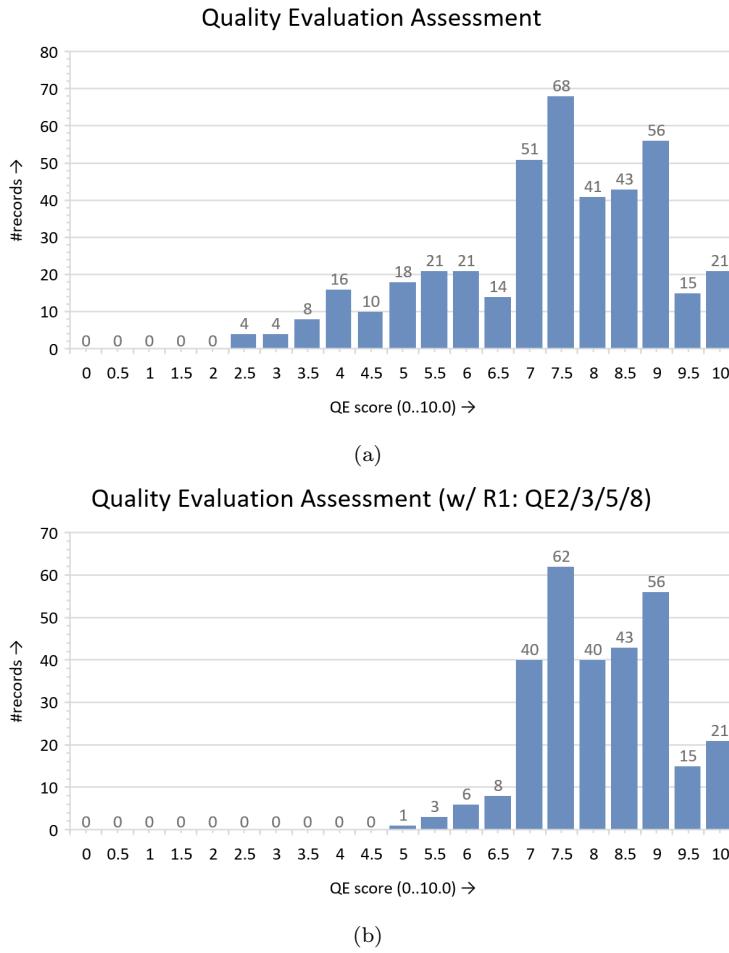


Figure 2: Distribution of the quality evaluation scores obtained from assessing the eligible works considered in the review: (a) all eligible works; (b) works that pass the rejection criterion during the QE assessment related to $\text{QE2/3/5/8} = 0.0$ (no compliance).

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 publishers⁴. 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 mapping⁷. 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 computing⁸ 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 tool⁹ 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 manual¹⁰ (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/>

¹⁰https://www.vosviewer.com/documentation/Manual_VOSviewer-1.6.8.pdf

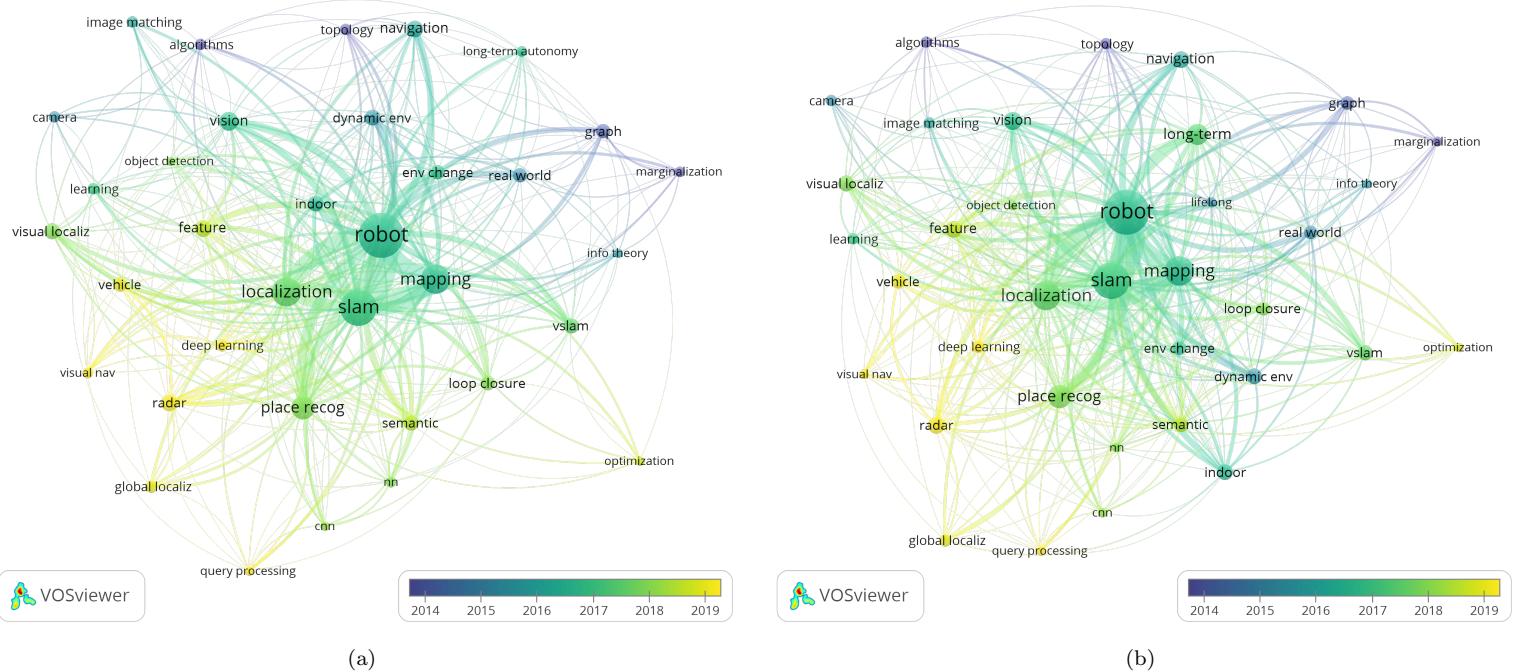


Figure 3: Keywords co-occurrence analysis on the 144 included records generated by VOSviewer with overlay visualization by the average publication year: (a) original keywords; (b) all keywords containing long-term and lifelong summarized by the terms themselves. Parameters used for generating the co-occurrence 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 localiz** (**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 keyword 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 minimum of 3 co-authored documents there is not a connection between these 8 clusters. Even so, the graph presented in Figure 4

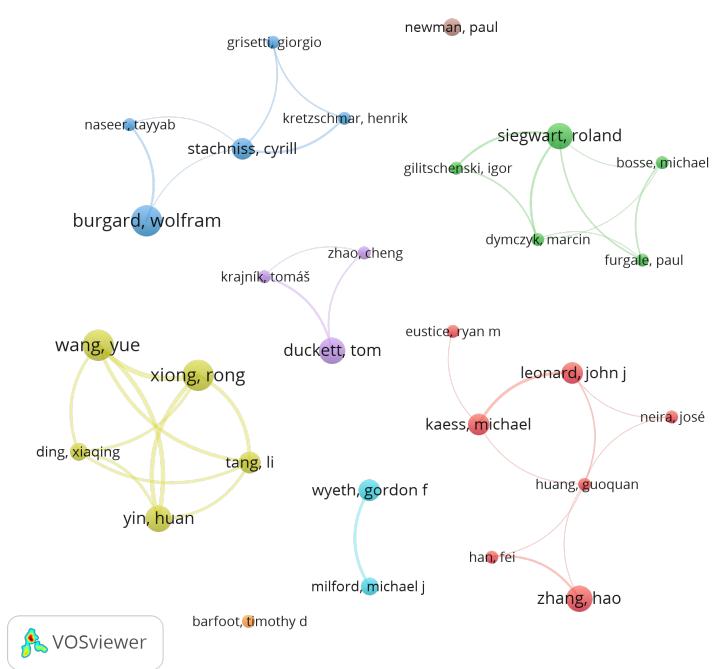


Figure 4: Co-authorship analysis on the 144 included records generated by VOSviewer. Parameters used for generating the co-occurrence network: minimum number of occurrences = 3, attraction = 2, repulsion = -3, scale = 1.49, circles size variation = 1.0, lines size validation = 1.0.

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 bias 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.

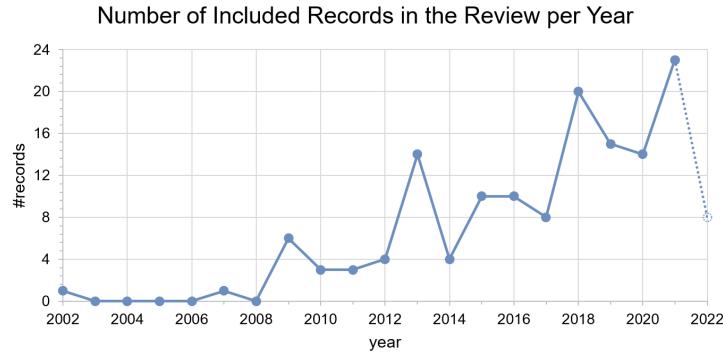


Figure 5: Evolution of published records per year considering the 144 included records in this review

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 gained 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 2015¹¹. 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

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

| Journal | Year | | | |
|---|-------|----------|------|----|
| | 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 |

| Conference | Year | | | |
|--|-------|----------|------|----|
| | 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 (RO-BIO) | 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 |

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.

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, re-

¹¹<https://www.ieee-ras.org/publications/ra-1>

spectively. 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/w/m/y equivalent to day/week/month/year, 0 if only 1 run), and seq. – number of sequences of the dataset.

| Dataset | Year | Long-term lighting day/night weather seasonal dynamics sparsity | Environ. | Domain | Sensor | | | | | | Calib. | GT data | Format | dist. (km) | path (km) | time (h) | int. (d/w/m/y) | #seq. | | |
|-----------------------------------|------|---|-----------------|----------------------------------|------------------------------|--|-----------------|-----------|--------|------|--------|---------|--------------------------|---|-----------|-----------|----------------|-------|-------|----|
| | | | | | odo | gray | color | monocular | stereo | omni | | | | | intrinsic | extrinsic | | | | |
| FHW | 2001 | x | indoor (museum) | ground (TOUR-BOT) | x | | | | | | | | – | CARMEN | – | – | 1.98 | – | 1 | |
| FR079 | 2003 | x | indoor (office) | ground (robot) | x | | | x | | | | | – | CARMEN | – | – | 0.29 | – | 1 | |
| FR101 | 2003 | x | indoor (office) | ground (robot) | x | | | x | | | | | – | CARMEN | – | – | 0.29 | – | 1 | |
| Intel Research Lab 2003 | 2003 | x | indoor (office) | ground (robot) | x | | | x | | | | | – | CARMEN | 0.506 | – | 0.75 | – | 1 | |
| MIT Killian Court | 2004 | x | indoor (office) | ground (robot) | x | | | x | | x | | | – | CARMEN | 2.2 | – | 2.5 | – | 1 | |
| City Center (FAB-MAP) | 2008 | x | x | outdoor (urban) | ground (robot) | x | x | | | | x | x | GPS, manual | plain text (non-image), jpg (image) | 2 | – | – | – | 1 | |
| Lip6Indoor | 2008 | | | indoor (office) | ground (hand-held) | x | x | | | | | x | manual | ppm (images) | – | – | 0.11 | – | 1 | |
| Lip6Outdoor | 2008 | x | x | outdoor (campus) | ground (hand-held) | x | x | | | | | x | manual | ppm (images) | – | – | 0.3 | – | 1 | |
| New College (FAB-MAP) | 2008 | x | x | outdoor (campus) | ground (robot) | x | x | | | | x | x | GPS, manual | plain text (non-image), jpg (image) | 1.9 | – | – | – | 1 | |
| St Lucia Bris-bane 2008 | 2008 | x | x | outdoor (urban) | ground (car) | x | x | | | | | | – | – | 66 | – | 1.67 | – | 1 | |
| Bicocca (indoor) | 2009 | x | x | indoor (office) | ground (Robo-com) | x | x | x | x | x | x | x | map model, laser-based | plain text (non-image), png (image) | – | – | 2.5 | 3d | 5 | |
| COLD | 2009 | x | x | x | indoor (office) | ground (Pioneer 3, ATRV Mini, PeopleBot) | x | x | x | x | x | x | laser-based, manual | plain text (non-image), jpg (image) | 0.92 | – | 0.99 | – | 76 | |
| Malaga 2009 | 2009 | x | x | outdoor (parking, campus) | ground (car) | x | x | | x | x | x | x | RTK-GPS | Rawlog MRPT | 6.358 | – | – | – | 6 | |
| New College | 2009 | x | x | outdoor (campus) | ground (Segway) | x | x | x | x | x | x | x | GPS | plain text (non-image), png (stereo), jpg (omni) | 2.2 | – | 0.73 | – | 1 | |
| albert-b-laser-vision | 2010 | x | | x | indoor (office) | ground (iRobot B21r) | x | x | x | x | | | – | CARMEN (non-image), jpg (image) | – | – | 0.18 | – | 1 | |
| CMU-VL | 2011 | x | x | x | outdoor (urban) | ground (car) | x | x | | | x | x | x | GPS | – | – | 8.5 | – | 1y 16 | |
| Ford Campus | 2011 | x | | x | outdoor (campus, urban) | ground (car) | x | x | x | x | x | x | RTK-GPS | LCM log | – | – | – | 2m | – | |
| UTIAS Multi-Robot | 2011 | x | | indoor (empty space) | ground (Create) | x | x | x | | | | x | external tracking system | jpg (image), dat (non-image) | – | – | 4.78 | – | 9 | |
| Alderley Bris-bane | 2012 | x | x | x | outdoor (urban) | ground (car) | x | x | | | | | manual | – | 16 | 8 | – | – | 2 | |
| TUM RGBD | 2012 | x | x | indoor (office, industrial hall) | ground (handheld, Pioneer 3) | x | x | x | | x | x | x | external tracking system | plain text (non-image), png (image + depth), ROS bag | 0.285 | – | 0.35 | – | 15 | |
| CoBots long-term | 2013 | x | x | x | indoor (office) | ground (robot) | x | x | x | x | | x | – | ROS bag | 131 | – | 260 | 2y3m | 1082 | |
| KITTI | 2013 | x | x | x | outdoor (urban) | ground (car) | x | x | x | x | x | x | RTK-GPS | png (image), binary (laser), plain text (imu, gps) | – | – | 1.18 | 8d | 61 | |
| MIT Stata Center | 2013 | x | x | x | indoor (office) | ground (PR2) | x | x | x | x | x | x | map model | ROS bag | 42 | – | 38 | 1y9m | 84 | |
| Nordland | 2013 | x | x | x | outdoor (railway) | ground (train) | x | x | | | x | | GPS | mp4 (video stream), plain text (gps) | 2916 | 729 | 39.74 | – | 4 | |
| Gardens Point Campus of QUT | 2014 | x | x | x | indoor, outdoor (campus) | ground (hand-held) | x | x | | | | | ground-plane position | png (images), plain text (ground plane) | – | – | – | – | 3 | |
| Witham Wharf RGB-D (LCAS STRANDS) | 2014 | x | x | x | indoor (office) | ground (SCITOS-G5) | x | x | x | x | | x | – | ROS bag | – | – | – | 1y1m | 368 | |
| KAIST | 2015 | x | x | x | outdoor (urban) | ground (car) | x | x | x | x | x | x | RTK-GPS | png (images), plain text (imu, gps) | 84 | – | – | 18d | 36 | |
| EuRoC | 2016 | x | | indoor (industrial hall, office) | air (AscTec Firefly) | x | x | x | | | x | x | x | external tracking system | ROS bag | 0.8936 | – | 0.37 | – | 11 |
| NCLT | 2016 | x | x | x | x | indoor, outdoor (campus) | ground (Segway) | x | x | x | x | x | RTK-GPS, SLAM-based | binary (laser), tiff (image), plain text (non-laser or image) | 147.4 | – | 34.9 | 1y4m | 27 | |
| Berlin damm | 2017 | x | x | x | outdoor (urban) | ground (car) | x | x | | | | | manual | jpg (image) | – | – | – | – | 2 | |
| Oxford Robot-Car | 2017 | x | x | x | x | outdoor (urban) | ground (car) | x | x | x | x | x | RTK-GPS | png (image), binary (laser), plain text (imu, gps, odo) | 1010.46 | 10 | – | 1y8m | 133 | |
| YQ21 | 2017 | x | x | x | outdoor (campus) | ground (car) | x | x | x | x | x | x | RTK-GPS | binary (laser), jpg (images), plain text (gps) | 23 | – | 6.5 | 1w | 21 | |
| CMU-Seasons | 2018 | x | x | x | x | outdoor (urban) | ground (car) | x | x | | x | x | manual | jpg (image) | – | 8.5 | – | 330d | 17 | |
| Freiburg Across Seasons | 2018 | x | x | x | x | outdoor (urban) | ground (car) | x | x | | | x | GPS, manual | jpg (image) | 110 | – | – | 3y | 3 | |
| RobotCar Sensors | 2018 | x | x | x | x | outdoor (urban) | ground (car) | x | x | x | x | x | manual | jpg (image) | – | 10 | – | 178d | 10 | |
| Bonn RGB-D Dynamic | 2019 | | x | indoor (office) | ground | x | x | x | | | x | x | external tracking system | png (images, depth), plain text (imu, gps) | – | – | – | – | 26 | |
| CBD | 2019 | x | x | x | outdoor (urban) | ground | x | x | x | | | | manual | png (images) | – | – | – | – | 1 | |
| MulRan | 2020 | | x | outdoor (urban) | ground (car) | x | | | x | x | x | x | SLAM-based | binary (laser), CSV (global pose, radar ray), png (radar polar image) | 41.2 | – | – | 2m15d | 12 | |

Table 6: continued from previous page

| Dataset | Year | Long-term lighting day/night weather seasonal dynamics sparsity | Environ. | Domain | Sensor | | | | | | | | | | Calib. | GT data | Format | dist. (km) | path (km) | time (h) | int. (d/w/m/y) | #seq. | | | |
|-----------------------|------|---|--------------------------|------------------------|--------|---------|-------|-----------|--------|------|------|---------|----|---------|--------|---------|--------|------------|--------------------------|---|----------------|-------|------|--------|---|
| | | | | | odo | gray | color | monocular | stereo | omni | RGBD | thermal | 2D | 3D | radar | sonar | IMU | GPS | intrinsic | extrinsic | | | | | |
| Oxford Radar RobotCar | 2020 | x x x x | outdoor (urban) | ground (car) | x | x x x x | | | | | | | x | x x x x | x | x x x x | x | x x x x | RTK-GPS, SLAM-based | png (image, raw laser, radar), binary (laser), plain text (imu, gps, odo) | 280 | 10 | — | 1m 32 | |
| USyd Campus | 2020 | x x x x x | outdoor (campus) | ground (car) | x | x x | | | | | | | x | x x x x | x | x x x x | x | x x x x | GPS | ROS bag | — | — | — | 1y 52 | |
| IPLT | 2021 | x x x x x | outdoor (parking) | ground (car) | x | x x | | | | | | | x | x x x x | x | x x x x | x | x x x x | GPS | ROS bag | — | 0.2 | — | 2y 127 | |
| RADIATE | 2021 | x x x x | outdoor (parking, urban) | ground (car) | | x x x | | | | | | | x | x x x x | x | x x x x | x | x x x x | RTK-GPS | ROS bag | — | — | 4.98 | — | |
| NTU VIRAL | 2022 | x | indoor, (campus) | outdoor air (DJI M600) | | x x x | | | | | | | x | x x | x | x x | x | x x | external tracking system | ROS bag | 1.845 | — | 0.9 | — | 9 |

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-expose | multi-view | multi-camera | sensor | exp. self-acq. | ground-truth | dis. (km) | time (h) | path (km) | 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 | 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 | 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 | 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 | 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 |
| Pirkar 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 | 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 | 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: appearance dynamic sparsity | 2: multi-session computational intentional | 3: | 4: multi-rode | 5: offline | 6: online | 7: water outdoor | 8: exp. self-eval. | 9: ground-truth | 10: dist. (km) | 11: int. (d/m/m/y) | 12: |
|--|---|---|---|------------------|---------------|--------------|---|----------------------------|--------------------|-------------------|-----------------------|---|
| Ref. | | | | | | | | | | | | |
| Churchill and Newman 2013 | x | visual odometry (3D, 6DoF) experience (graph, local views, observability edges) | - | x x x | x | x | camera (color, stereo) | x RTK-GPS | - | 37 | 0.7 | - |
| Pomerleau et al. 2014 | x | point cloud matching (3D, 3DoF) | - | x x x | x | x | wheel odometry, laser (3D) | x map, targeted speed | 3.9 | 1.3 | - | 7m |
| Murphy and Sibley 2014 | x x | image classification (location) | - | x x x | x | x | camera (color, mono) | x - | - | - | - | 1w New College |
| 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 |
| Williams et al. 2014 | x | odometry (3D, 6DoF) | pose graph (graph) | - | x x x | x x | wheel odometry, camera (color, stereo), IMU (2D) | x RTK-GPS, simulation | - | - | - | - KITTI |
| Einhorn and Gross 2015 | x x | odometry | pose graph (graph, 2D/3D NDT) | - | x x x | x | camera (mono, RGBD), laser (2D) | x - | 7 | - | 3 | 2d |
| Pérez et al. 2015 | x | particle filter (3D, 6DoF) | pose graph (graph, 6DoF edges) | - | x x x | x x | wheel odometry, camera (gray, stereo), laser (2D) | x SLAM-based | 11.5 | - | 3.5 | - |
| Li et al. 2015 | x x | feature matching (location) | pose graph (graph) | - | - - | x | camera (gray, mono) | x manual | - | - | - | 3y - |
| 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 |
| Dymczyk, Lnen, et al. 2015 | x | feature matching (location) | keyframe (graph) | - | x x | x x | camera (mono) | x no pruning | 1.034 | - | - | 10d - |
| Rapp et al. 2015 | x | particle filter (2D, 3DoF) | grid (occupancy, 2D) | - | - - | x x | odometry, radar | x - | - | - | - | - |
| Vysotska et al. 2015 | x | image sequence matching (location) | database (images, sequence) | - | - - | x x | camera (color, mono) | x manual | 3 | - | - | - |
| Neubert et al. 2015 | x | feature matching (location) | dictionary (translation, winter + summer) | - | - - | x x | camera (color, mono) | - - | - | - | - | Nordlandsbanen |
| Mur-Artal et al. 2015 | x | bundle adjustment (3D, 6DoF) | keyframe (graph) | - | x x | x x | camera (gray, mono) | - - | - | - | - | KITTI, New College, TUM RGBD |
| Naseer, Suger, et al. 2015 | x | image sequence matching (location) | - | - | x x | x x | camera (color, mono) | x GPS | - | - | - | - |
| Karaoguz and Bozma 2016 | x | feature matching (location) | pose graph (graph, similarity edges) | - | x x x | x x | camera (color, mono) | x - | 0.325 | - | - | - |
| Santos et al. 2016 | x | - | grid (occupancy, 3D) | - | x x | x | camera (RGBD) | x simulation | - | - | - | 5d - |
| 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 |
| Dymczyk, Schneider, et al. 2016 | x | - | keyframe (graph) | - | x x | x x | camera, IMU | x SLAM-based | - | 0.15 | - | - |
| Gadd and Newman 2016 | x x | visual odometry (3D, 6DoF) | experience (graph, local views, 6DoF edges) | x x x | x x x | x | camera (grey, mono) | x - | 100 | - | - | 1m - |
| 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 x | camera (gray, mono), IMU, DVL | x map model | 10.159 | - | - | 3y - |
| 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 - |
| 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 | - |
| Taisho and Kanji 2016 | x | image classification (location) | database (images, image features) | - | - - | x x | camera (color, mono) | x manual | - | - | - | - |
| Han, X. Yang, et al. 2017 | x | feature matching (location) | - | - | x x | x x | camera (color, mono) | - - | - | - | - | CMU-VL, Nordlandsbanen, St Lucia 2007 |
| 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 | - | - | - | - |
| Griffith and Pradalier 2017 | x x x | SIFT flow (3D, 6DoF) | pose graph (graph, 6DoF edges) | - | x x | x x | camera (color, mono), GPS, IMU | x manual | 100 | - | - | 1y2m - |
| Naseer, Oliveira, et al. 2017 | x | feature matching (location) | - | - | x x | x x | camera (color, mono) | x manual | 100 | - | - | 3y - |
| Krajník, Fentanes, Santos, et al. 2017 | x | - | grid (occupancy, 3D) | - | x x x | x x | camera (RGBD) | x external tracking system | - | - | - | 112d NCLT, Witham Wharf RGB-D |
| Ila et al. 2017 | x | odometry (3D, 6DoF) | pose graph (graph) | - | x x x | x x | - | - simulation | - | - | - | - KITTI pose error, #nodes |
| Latif, Huang, et al. 2017 | x x | dictionary search (location) | dictionary (incremental) | - | x x 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 computational complexity, f-score, precision-recall |
| Bescos et al. 2018 | x | bundle adjustment (3D, 6DoF) | keyframe (graph) | - | x 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 | x | camera (color, mono) | - - | - | - | - | CMU-VL, Nordlandsbanen, St Lucia 2007 precision-recall |
| Han, Beleid, et al. 2018 | x | feature matching (location) | - | - - | x x | x x | camera (color, mono) | - - | - | - | - | CMU-VL, Nordlandsbanen precision-recall |

Table 7: continued from previous page

| DE: | 1: appearance dynamic sparsity | 2: multi-session computation | 3: | 4: multi-rode | 5: offline | 6: online | 7: water | 8: exp. self-ecc. | 9: ground-truth | 10: dist. (km) | 11: int. (d/m/m/y) | 12: | | | |
|----------------------------------|---|--|---|----------------------|---------------|--------------|-------------|----------------------|--|-------------------|-------------------------------------|-----------------|--|---|--------------------------------|
| Ref. | localization | mapping | sensor | multi-rode | offline | online | water | exp. self-ecc. | ground-truth | dist. (km) | int. (d/m/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 | x | wheel odometry, laser (2D, 3D), IMU | - | 1d | - | execution time, precision-recall | | |
| Nobre et al. 2018 | x | Mahalanobis distance minimization (2D, 3DoF) | feature | - | x | x | x | x | wheel odometry, camera (color, mono) | 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 | 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 | - | - | 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 | 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 | - | - | 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 | 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 | x | wheel odometry, camera (mono) | - | - | - | KITTI execution time, pose error | | |
| Siva and Hao Zhang 2018 | x | feature matching (location) | - | - | - | x | x | x | camera (omni) | x | GPS | 19.15 - - 1y | - | precision-recall | |
| Lüthardt 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 | x | camera (color, mono) | - | - | - | Nordlandsbanen, St Lucia 2007 precision-recall | | |
| Yu et al. 2019 | x | vocabulary hashing (location) | - | - | - | x | 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 | 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 | 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 | 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 | 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 | 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 | wheel odometry, sensor (gray, mono) | x | - | - | - | 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 | 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 | x | laser (2D) | x | SLAM-based | - | - | - | execution time, pose error |
| Schmuck and Chli 2019 | x | odometry (3D, 6DoF) | keyframe (graph) | - | x | x | x | x | camera, IMU | - | - | - | EuRoC pose error | | |
| Ganti and Waslander 2019 | x | bundle adjustment (3D, 6DoF) | keyframe (graph) | - | - | x | x | x | camera (stereo) | - | - | - | KITTI pose error | | |
| Ding, Y. Wang, Tang, et al. 2019 | x x | EKF (3D, 6DoF) | keyframe (graph) | - | x | 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 | 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 | 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 | 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 | | |
| Karaoguz and Bozma 2020 | x | - | pose graph (graph) | x | x | x | x | x | camera (mono) | x | - | - | COLD computational complexity, 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 computation | localization | mapping | | | | exp. self-correct. | ground-truth | | datasets | metrics | | |
| H. Yin, Y. Wang, et al. 2020 | x | x | particle filter (2D, 3DoF), pose graph (graph, 6DoF), point cloud matching (3D, 6DoF) | - | x | x | x | - | - | - | 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 | - | precision-recall | |
| T. Qin et al. 2020 | x | | EKF (2D, 3DoF) | feature (semantic) | - | 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 | bundle adjustment (3D, 6DoF) | point cloud (3D) | - | 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 | laser (3D) | - | - | KITTI, NCLT | pose error | |
| B. Liu et al. 2021 | x | | EKF (3D, 6DoF), feature matching (location) | keyframe (graph) | - | 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 | - | memory, pose error | |
| Derner et al. 2021 | x | | feature matching (3D, 6DoF) | database (images, features, pose) | - | x | x | x | wheel odometry, camera (RGBD) | x | manual | 0.198 - - - | Witham Wharf RGB-D | |
| 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 | - | 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 | wheel odometry, laser (3D) | x | simulation | - | confusion matrix, execution time, precision-recall | |
| Berrio, Worrall, et al. 2021 | x | - | | grid (feature, 2D) | - | - | - | 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 | 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 | 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 | |
| Meng et al. 2021 | x | | laser odometry (3D, 6DoF) | pose graph (graph) | - | x | x | x | laser (3D) | - | - | - | ATE, execution time, pose error | |
| S. Zhu et al. 2021 | x | | particle filter (2D, 3DoF) | grid (occupancy, 2D) | - | 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 | camera, laser (3D) | x | - | - | 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 | - | execution time, precision-recall | |
| Coulin et al. 2022 | x | | EKF (3D, 6DoF) | magnetic (vector) | - | 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 | - | execution time, precision-recall | |

Table 7: continued from previous page

| DE: | 1: appearance dynamic sparsity | 2: multi-session computation | 3: localization | 4: mapping | 5: sensor | 6: water mark | 7: ground-truth | 8: exp. self-corr. | 9: int. (x/m/y) | 10: path (km) dist. (km) | 11: datasets | 12: metrics |
|-----------------------------------|---|--|--------------------|---------------|-------------------------------------|---------------------|---------------------|-----------------------|--------------------|--------------------------------|----------------------------------|--|
| Ref. | | | | | | | | | | | | |
| T.-M. Nguyen, M. Cao, et al. 2022 | x | bundle adjustment, sensor fusion (3D, 6DoF) | - | - | 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 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 x x | 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 | 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 x x | x x x | radar | - | - | - | MulRan, Oxford RobotCar, RADIATE | ATE, execution time, pose error |