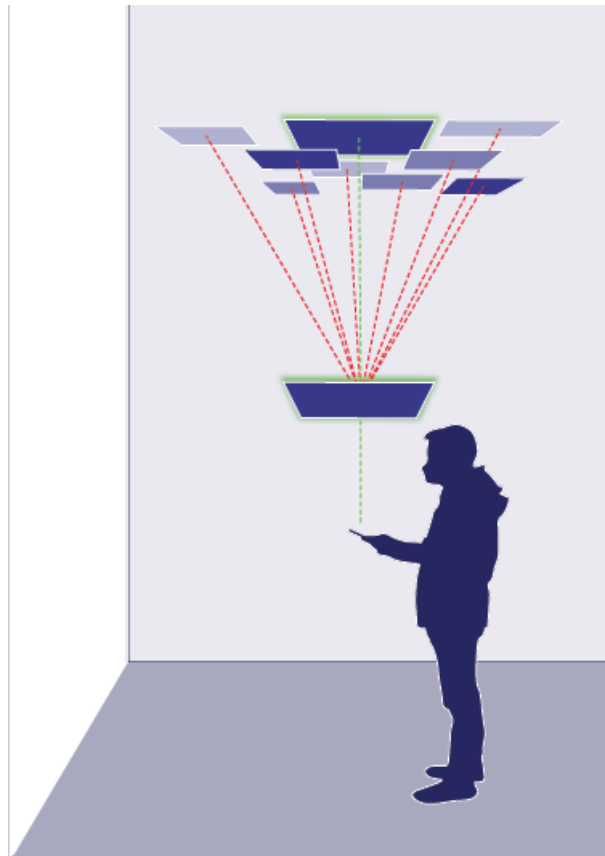


Indoor localisation in semi-public buildings based on LiDAR point clouds of the ceilings

Ioannis Dardavesis
student #5372666

1st supervisor: Edward Verbree
2nd supervisor: Azarakhsh Rafiee

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1 Introduction

Nowadays, the evolution of localisation and navigation technologies is vast, aiding towards facilitating users' guidance in various environments. Outdoor positioning can be easily achieved, with the widely used Global Navigation Satellite Systems (GNSS), which are included in every person's mobile device. However, due to the presence of high buildings in dense urban environments and bad reception in indoor environments, alternative ways of positioning and localisation respectively, need to be explored.

Even during the early centuries, when the recent technological discoveries were not available, localisation and navigation were important fields, that could not be adequately tackled, even by the most renowned scientists of that era. The calculation of a relative position within a coordinate reference system, based on star observations was an initial attempt to comprehend a person's location in space, as sailors needed to navigate towards their final destination. The maps of those eras, were giving a sense of location, as identifiable objects were linked to relative positions of the users (Sobel, 1998). In both of the aforementioned examples, landmarks are introduced in an attempt to accomplish localisation.

Landmarks play a significant role in both outdoor and indoor space. Salient objects, such as high-rise buildings facilitate guidance in outdoor environments. In these environments, landmarks can be both local and distant depending on the visibility, in contrast to the indoor space where corners and walls tend to block the user's vision. Indoor spaces contain regular geometries (room boundaries), as opposed to the outdoor space (Yang and Worboys, 2011). These points have to be taken into consideration, showing that different strategies have to be followed, as a means to accomplish indoor and outdoor landmark-based localisation.

Regarding indoor environments, the lower density of landmarks and the absence of outstanding elements can result to easier loss of orientation, compared to outdoors (Michon and Denis, 2001). Localisation comprises an important problem in public buildings, such as airports or train stations, that usually consist of chaotic spaces, leading to a higher chance that the user will become confused and lose his orientation. In that context, artificial landmarks (signs) as well as natural landmarks (plants) can help the user retrieve his location. In addition, landmarks can also be used as an affirmation that the user is on the correct route towards the final destination (Hile and Borriello, 2008). Indoor localisation could also be applied to deal with emergency situations, such as fires in complex indoor spaces. First-aid responders need guidance, related to the location of the person in need, as well as a way to reach that location (Yang and Worboys, 2011).

The challenge of achieving indoor localisation in different environments, is to find a technique that does not depend on costly and hard to access indoor sensor networks, such as Wi-Fi fingerprinting or Bluetooth, but to make use of features that are accessible to everyone in each user's mobile device (Willems, 2017). Currently, various applications have emerged for precise localisation, that use triangulation and trilateration of users based on Bluetooth, Wi-Fi (Baniukevic et al., 2013) and other types of sensors such as Arduino (Mitilineos et al., 2010) and Raspberry Pi, as well as applications that use optic sensors to achieve object recognition (Google Lens). It has to be noted that these applications work on a more local level compared to outdoors, therefore localisation provides contextual information on someone's location in a sub-room or room level. These aforementioned applications have eased the localisation process and made it accessible to more users.

1.1 Scientific Relevance

A lot of research has been implemented in the field of outdoor navigation and localisation, in contrast to indoor environments, where the developments are relatively new and mostly involve Bluetooth sensors and Wi-Fi fingerprinting, which requires an up-to-date radio map, in an effort to achieve localisation. Therefore, there is space for innovation by utilising other techniques, that take into advantage camera and LiDAR sensors. Especially the use of LiDAR sensors, which is an acronym for "light detection and ranging", is rapidly increasing, as they were recently included in the latest releases of Apple's iPhone and iPad devices, showing that they will be a major part of the mobile devices that will follow during the upcoming years. The aforementioned sensors are accessible to every person that owns a mobile phone (at least in the case of cameras), therefore localisation becomes accessible to everyone.



Figure 1: LiDAR sensor of iPhone 12 pro

2 Related work

This section will provide an overview of the implemented research that is related to this thesis. This research consists of the following primary parts: a) indoor localisation b) point cloud registration and c) image matching techniques. The relevance and differences of each scientific paper and the current thesis will be discussed at the end of each corresponding section.

2.1 Exploring a pure landmark-based approach for indoor localisation

This related research is based on a MSc Geomatics thesis, implemented by (Willems, 2017) at TU Delft. It involves the establishment of a framework that will use landmarks to perform indoor localisation and will become the basis for indoor navigation. Defining landmarks, discussing their reliability for indoor localisation and their geometric integration in a database are significant points that are discussed in this research. Moreover, the author explores how the number and the constellation of landmarks affects the localisation, and also presents primary results on whether a pure-landmark based approach can be used for navigation. Two cases are tested; one artificial and one natural case, in order to discover a user's location based on the visibility of the landmarks from a certain viewpoint, while taking into account that their location is known.

The project of (Willems, 2017) is complementary to this thesis research, as it focuses on the use of landmarks for indoor localisation as a basis for navigation, and examines their suitability to achieve this task. The author discusses the reliability of different landmarks that exist in indoor environments, as opposed to this thesis that will only focus on ceilings. Moreover, isovist and landmark visibility analysis are not concepts that will be taken into account during this thesis research. Aside from the part concerning localisation, this thesis will use the current and previous locations of different users, in an effort to track and trace the paths that they use and discover different movement patterns during different times of a day, in an anonymous way that will respect the privacy of the users.

2.2 Indoor localisation based on point clouds of the ceiling

This related research, was a part of the course "Synthesis Project", which is included in the MSc Geomatics course syllabus of TU Delft (Fratzeskou et al., 2019). It describes an indoor localisation method, where users acquire data, such as images, videos and point clouds of the ceilings to retrieve their current location. The choice of the ceilings lies on the fact that they usually do not change over time, as well as due to the existence of different installations that describe each room in a unique way. Specifically, the authors discuss a methodology, where point clouds of ceilings are uploaded in a database and each of them represents different rooms. User-acquired data is translated into a point cloud and then based on its unique signature, it is compared with all the other point clouds of the database. The best match will show in which room the user is located. The signatures of point clouds are found, based on two methods: feature and histogram matching, as well as the integration of these methods. The goal of this project is to compare the aforementioned methods, based on their results and decide if this pipeline can lead towards achieving adequate indoor localisation results from ceiling data.

In that project, similarly to this thesis, the use of ceiling data for indoor localisation purposes is discussed, however there are some differences. First, this thesis will contain a real-time comparison between the user and database point clouds, while the data will come solely by a LiDAR camera of an iPhone device. Last but not least, the results of the indoor localisation, will be used in order to track and trace user locations in public buildings, in order to discover possible movement patterns at different times of a day.

2.3 ICP registration based on 3D point clouds feature descriptor

This paper written by (He et al., 2021) discusses a point cloud registration method that can be applied in 3D modelling, reverse engineering and various other fields. The point registration method that aims to find the translation and rotation matrix between point clouds, uses the Iterative Closest Point (ICP) algorithm, one of the most common point cloud registration techniques. However, due to the fact that this algorithm requires a good initial value, meaning that the point clouds need to be already similar to each other, a different pipeline is developed. The algorithm takes into advantage the local features of the point clouds and attempts to match them, using a three-dimensional descriptor, that combines density curvature and their normal information. Therefore, an initial registration is performed and afterwards the ICP algorithm is used in order to improve the result, in terms of quality and time efficiency.

The proposed methodology of this paper considers a point cloud registration technique, that will be partly used during this thesis research in order to compare user and database point clouds of the rooms' ceilings. Consequently, the best match between point clouds will result into the localisation of the user.

2.4 A novel point cloud registration using 2D image features

This paper composed by (Lin et al., 2017), analyses an approach to perform a three-dimensional registration method based on two-dimensional features. Specifically, the point clouds are transformed into two-dimensional bearing angles, while feature matching with the Speeded Up Robust Features (SURF) technique is performed, in an effort to find matching pixel pairs between two images. Based on that pairing, the calculation of the rotation matrix between the two images is calculated, by a least squares approximation. The results of this research show that the quality is similar to the ICP algorithm discussed above, with a reduced computation cost.

The relevance of this research to the current thesis lies in the proposed two-dimensional feature matching method that is proposed. Instead of transforming point clouds to two-dimensional bearing angle images, digital surface models of the ceilings will be created. Afterwards, they will be matched using the SURF algorithm, as well as others that are not discussed in the aforementioned paper.

3 Research questions

Defining the main and secondary research questions, is a crucial part with the aim of addressing indoor localisation and ensure the concreteness of this project. Therefore, the primary research question is formed as follows:

"To what extent can ceilings with characteristic details be used for indoor localisation purposes?"

In order to have a better understanding of the concept and be able to answer the main research question robustly, some complementary research questions are formed.

1. *"Which parameters (measuring angle, height, part of the room) should the user take into account while acquiring point clouds of ceilings?"*
2. *"Which is the optimal image matching algorithm to achieve indoor localisation from ceiling data?"*
3. *"Does integration of point and image matching techniques improves the results of localisation?"*
4. *"Are LiDAR point clouds acquired by an iPhone device an accurate and accessible solution towards indoor localisation?"*
5. *"Can the proposed pipeline aid towards facilitating localisation in emergency situations?"*
6. *"How can we assess and compare the results of different methods?"*

3.1 Objectives and Scope

This research is implemented, in order to explore the possibility of the ceilings in public or semi-public buildings, being used for indoor localisation purposes. The latter is a fundamental step and is considered as the basis towards achieving indoor navigation. Therefore, this research focuses on localisation, as well as track and tracing of different users' positions for the purpose of discovering different movement patterns and not on navigation, which will be a part of the future work recommendations of this thesis. Additionally, the case study will take place in the Faculty of Architecture and the Built Environment at TU Delft, that consists

of rooms. whose ceilings include installations, that can aid towards revealing the unique identity of each room. As a result, the recommended pipeline can not be applied to ceilings that do not consist of characteristic details. Data acquisition and specific instructions on how a user can perform it, in order to achieve optimal results will be also included. LiDAR sensors incorporated in the latest iPhone devices and non-commercial applications will be used to acquire and manipulate point cloud data. The thesis will delve into the use of ceilings for indoor localisation, whereas their automatic detection will not be discussed. An additional focus of this research will be the implementation, assessment and integration of different image matching and point cloud registration techniques, as a means to obtain the optimal localisation results. Last but not least, a Minimum Viable Product of a web application could be produced, in order to visualise the results of this research.

This chapter will include an overview and an analysis of the proposed methodology that will be carried out during this thesis research, aiding towards answering the research questions that were established. The figure that is presented below (Figure 2) outlines the main steps that will be executed during this thesis research. Each of these steps will be extensively analysed in the following chapters.

Figure 2: Methodology Overview

The data for this project will be acquired using an iPad pro and an iPhone 12 pro device, by taking advantage of their LiDAR sensors. After considering and comparing different applications provided by Apple, the decision was to use the SiteScape app, an application that is available on the Apple Store and follows a freemium model, meaning that many of its basic capabilities are provided for free. Consequently, for the purposes of this research, this user-friendly and accessible app was preferred to other ones, that might have offered more

capabilities, but their nature is commercial. The point clouds that will be acquired from the SiteScape app, will be exported to a Polygon File Format (PLY), as this transformation is included in the basic and free version of the app. For the purpose of this thesis, point clouds of the ceilings of different rooms will be acquired and uploaded to a database, as well as point clouds taken by users, that want to find where they are located.

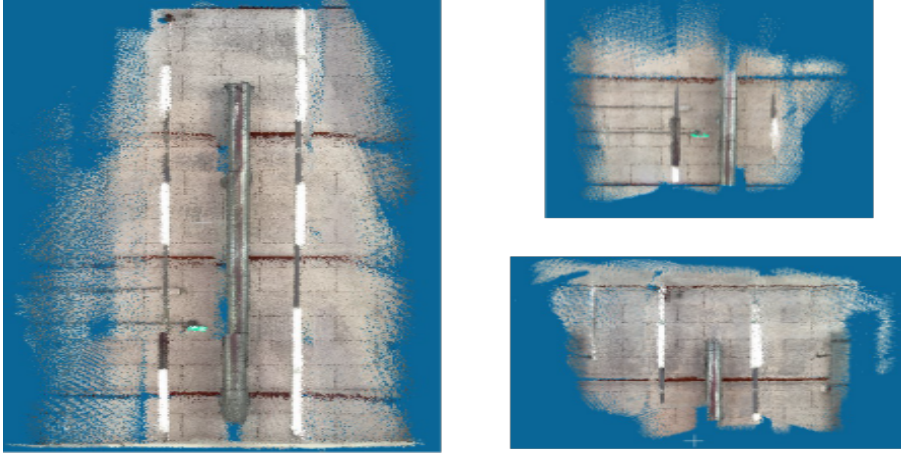
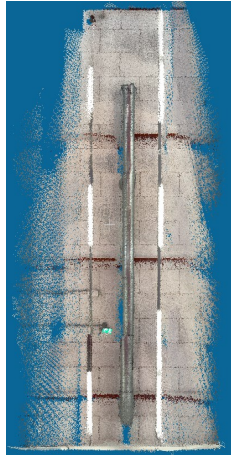


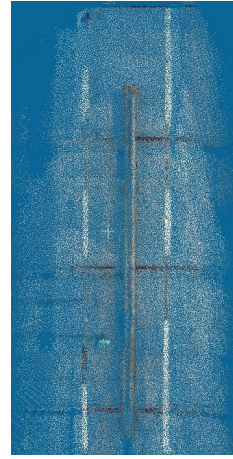
Figure 3: Example of a point cloud in the database (left) and two user-acquired point clouds (right)

4.2 Point cloud pre-processing

The comparison between these two types of point clouds can be facilitated by performing some primary operations. Pre-processing of the point clouds will include voxel downsampling, an operation where a regular voxel grid is used, to create a uniform downsampled point cloud, from an input point cloud. The algorithm is performed firstly by transforming points into voxels and secondly by generating the centroid of each voxel, which will be its representing point. This operation is useful, as it aims to reduce processing time by manipulating a point cloud of smaller size (Miknis et al., 2016). However, this operation has to be implemented carefully and until a certain threshold, because further downsampling might result to important loss of information. Furthermore, when acquiring ceiling data, it is possible that the point cloud includes adjacent wall parts, that need to be excluded from the upcoming operations. These parts can be considered as outliers (Han et al., 2017) for the purposes of this research. To achieve their removal, a smaller part of the acquired point cloud will be used, in an effort to discard the wall parts that might exist in the corners of the point clouds. Moreover, measurement errors may lead to the creation of shadow points in the cloud, that also have to be excluded (Guislain et al., 2016). Consequently, further filtering based on certain criteria might be needed, to finalize the pre-processing operations.



(a) Raw ceiling point cloud



(b) Pre-processed point cloud

Figure 4: Example of a raw point cloud and the result after processing

4.3 Point-cloud registration

After acquiring and pre-processing database and user point clouds, the next step is to create an algorithm that will attempt to compare them. The main idea behind this is, that each point cloud taken by a user, will be compared with all the point clouds in the database and the best match will reveal the room where the user is located. This procedure will work as follows for both types of point clouds. First, points with a unique and descriptive neighbourhood need to be detected. Afterwards, a descriptor for these points has to be computed. The descriptor can have different forms, such as a histogram, a value, or a multi-dimensional vector. For the point clouds, their descriptors will be compared, in order to find the best matches and fit them to each other. Additionally, the Random Sample Consensus (RANSAC) algorithm will be used to reject some correspondences and therefore refine the registration (Li et al., 2021). After performing the initial registration, in an attempt to improve the quality of the results and the time efficiency of the algorithm, the ICP algorithm will be implemented (Zhou et al., 2016). The further minimisation of the point cloud differences is performed by keeping one point cloud fixed, while the other is transformed towards it. Specifically, each point of the source point cloud is matched to the closest point of the reference point cloud. Then, rotation and translation are estimated and this process is iterated until the results converge. (Li et al., 2021). The user point cloud will be compared with all the database point clouds, based on the fitting and the RMSE value, which will result in the optimal localisation.

4.4 Image-matching

After the implementation of the aforementioned algorithms, that will co-register the compared point clouds, a point-to-raster interpolation method (Arun, 2013) will be executed, in order to create digital ceiling models from the database and user point clouds. Similarly to the down-sampling procedure, it is significant that the proper parameters will be used during this operation, so that no important information is omitted. An image-matching algorithm between these raster images will be implemented, to make the localisation results more robust, and also investigate if this additional algorithm improves them. The key points of the digital ceiling models will be found, based on different descriptors, such as ORB, SIFT or BRIEF (Vinay et al., 2015). Afterwards, the descriptors of the compared raster images will be matched using different image matching techniques, such as brute-force or FLANN. An extended comparison of the descriptors and the image matching algorithms is implemented by (Noble, 2016).

The number of matches and the similarity score between the user image and all the database images, will reveal the location of the user. Last but not least, except for the aforementioned metrics, histograms of the raster images, that express their unique signatures can also be used to make the result more concrete.

4.5 Storage

An indoor model of the test case, the Faculty of Architecture and the Built Environment of TU Delft, based on the work of (Spinoza Andreo et al., 2021) will be stored on the ArcGIS Online Server. The pre-processed point clouds that are representative of each room of the faculty and the respective digital ceiling models, will be uploaded to the server and will be attached to the correct room of this indoor model. Moreover, this indoor model will serve as an embedded map in the minimum viable product that will be created, allowing the users to have a visual insight of their location.

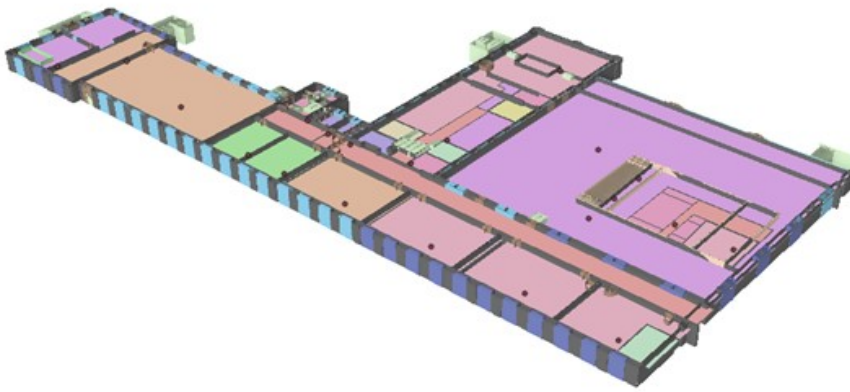


Figure 5: Indoor model of the Architecture Faculty

4.6 Web-app development-Minimum Viable Product

The visualisation of the results will have the form of a minimum viable product, such as a beta version of a web application. The database point clouds and the digital ceiling models will be requested from the ArcGIS server, in order to perform the localisation based on the comparison with the user data. Specifically, user acquired data will be posted in the app, revealing the name of the room where the user is located, as well as where the room is, based on the indoor model of the server.

4.7 Track and tracing

Each time the web application is used, the users' current and previous locations will be stored anonymously on the ArcGIS server. This information will help discovering different moving patterns, during different times of a day and will be visualised in the form of a heat-map. The latter will be based on a network graph of the building (Figure 6), that shows all the possible connections between its different rooms. To create this graph, CAD drawings of the different floors of the Faculty of Architecture and the Built Environment, that were also used for the creation of the indoor model of (Spinoza Andreo et al., 2021) will be manipulated accordingly in the ArcGIS software. The use of different colours on the lines of the network graph will reveal how much a path is used during a certain part of the day. This information could be

vital during this COVID-19 era, because it can be exploited by the building manager, who can achieve an optimal distribution of people in an indoor facility. (Spinoza Andreo et al., 2021).

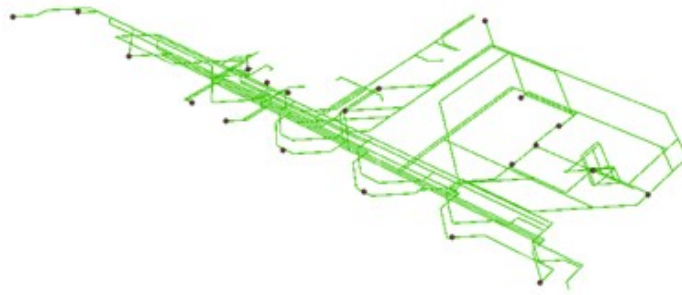


Figure 6: Network graph of the Faculty of Architecture and the Built Environment

4.8 Testing the algorithm in a sub-room level

An additional case will be tested in order to figure out if the proposed pipeline provides accurate results in a sub-room level. In order to achieve that, some rooms of the Faculty of Architecture and the Built Environment will be selected and subdivided into parts. This requires further point cloud acquisition of those room parts, as well as subdivision of the rooms in the indoor model of (Spinoza Andreo et al., 2021). The reasoning behind this testing lies in the interesting fact that in some cases, a user point cloud might be on the verge or overlaps more than one point clouds that belong to different room sections.

5 Time planning

| Start | End | Activity |
|--------|--------|---|
| 10 Sep | 12 Nov | Thesis topic formation |
| | | P1 - Registration of topics |
| 15 Nov | 31 Dec | Literature review |
| 15 Nov | 10 Dec | Review of different image matching algorithms |
| 10 Dec | 31 Dec | Review of different point cloud registration algorithms |
| | | P2 - Graduation plan (Formal assessment) |
| 7 Feb | 18 Feb | Data acquisition and pre-processing |
| 21 Feb | 11 Mar | Point cloud registration |
| 14 Mar | 25 Mar | Image matching |
| | | P3 - Midterm progress meeting |
| 28 Mar | 1 Apr | Database initialisation and organisation |
| 28 Mar | 15 Apr | Minimum viable product and testing |
| 18 Apr | 24 Apr | Track and tracing visualisation |
| 26 Apr | 20 May | Thesis writing |
| | | P4 - Go/no go (Formal assessment) |
| 25 May | 5 June | Finalize thesis report |
| 6 Jun | 20 Jun | Prepare thesis presentation |
| | | P5 - Public presentation and final assessment |

6 Tools and datasets used

Data will be acquired using the SiteScape app, that is available in the App Store for all users owning an iPhone or iPad device. Additionally, CAD drawings of the floors of the Faculty of Architecture and the Built Environment will be used as data to manipulate the existing indoor network of (Spinoza Andreo et al., 2021) and to create the network graph of Figure 6. The point cloud registration and image matching algorithms will be developed using Python programming language. Specifically, PCL and Open3D libraries will be used for point cloud pre-processing and registration, while the OpenCV library for image matching. The database including the rooms and their point clouds, as well as the digital ceiling models, will be created using ArcGIS Indoors and will be stored in the ArcGIS online server. Concerning, the front-end development of the minimum viable product a combination of javascript, html and css languages will be utilised.

References

- P. Arun. A comparative analysis of different dem interpolation methods. *The Egyptian Journal of Remote Sensing and Space Science*, 16(2):133–139, 2013. ISSN 1110-9823. doi: <https://doi.org/10.1016/j.ejrs.2013.09.001>. URL <https://www.sciencedirect.com/science/article/pii/S1110982313000276>.
- A. Baniukevic, C. Jensen, and H. Lu. Hybrid indoor positioning with wi-fi and bluetooth: Architecture and performance. volume 1, pages 207–216, 06 2013. doi: 10.1109/MDM.2013.30.
- C. Fratzeskou, C. Garg, K. Staring, M. Deng, C. Jansen, E. Verbree, and M. Meijers. Indoor localisation based on point clouds of the ceiling: Syntheses project 2019. 2019.
- M. Guislain, J. Digne, R. Chaine, D. KUDELSKI, and P. Lefebvre-Albaret. Detecting and Correcting Shadows in Urban Point Clouds and Image Collections. In *2016 International Conference on 3D Vision (3DV), Oct 2016, Stanford, United States*, Proceedings 2016 International Conference on 3D Vision (3DV), page 9p, Stanford, United States, Oct. 2016. URL <https://hal.archives-ouvertes.fr/hal-01393998>.
- X.-F. Han, J. Jin, M.-J. Wang, W. Jiang, L. Gao, and L. Xiao. A review of algorithms for filtering the 3d point cloud. *Signal Processing: Image Communication*, 57, 05 2017. doi: 10.1016/j.image.2017.05.009.
- Y. He, J. Yang, Z. Li, and B. Liang. Icp registration based on 3d point clouds feature descriptor. <https://doi.org/10.1117/12.2589460>, 11720:196–205, 1 2021. ISSN 1996756X. doi: 10.1117/12.2589460. URL <https://www.spiedigitallibrary.org/conference-proceedings-of-spie/11720/117200Q/ICP-registration-based-on-3D-point-clouds-feature-descriptor/10.1117/12.2589460.full>.
- H. Hile and G. Borriello. Positioning and orientation in indoor environments using camera phones. *IEEE Computer Graphics and Applications*, 28:32–39, 7 2008. ISSN 02721716. doi: 10.1109/MCG.2008.80. URL https://www.researchgate.net/publication/3210676_Positioning_and_Orientation_in_Indoor_Environments_Using_Camera_Phones.
- J. Li, Q. Hu, and M. Ai. Point cloud registration based on one-point ransac and scale-annealing biweight estimation. *IEEE Transactions on Geoscience and Remote Sensing*, PP:1–14, 01 2021. doi: 10.1109/TGRS.2020.3045456.
- C. C. Lin, Y. C. Tai, J. J. Lee, and Y. S. Chen. A novel point cloud registration using 2d image features. *Eurasip Journal on Advances in Signal Processing*, 2017:1–11, 12 2017. ISSN 16876180. doi: 10.1186/S13634-016-0435-Y/TABLES/1. URL <https://asp-eurasipjournals.springeropen.com/articles/10.1186/s13634-016-0435-y>.
- P.-E. Michon and M. Denis. When and why are visual landmarks used in giving directions? In D. R. Montello, editor, *Spatial Information Theory*, pages 292–305, Berlin, Heidelberg, 2001. Springer Berlin Heidelberg. ISBN 978-3-540-45424-3.
- M. Miknis, J. Ware, R. Davies, and P. Plassmann. Efficient point cloud pre-processing using the point cloud library. *International Journal of Image Processing*, 10(2):63–72, June 2016. ISSN 1985-2304.
- S. A. Mitilineos, D. M. Kyriazanos, O. E. Segou, J. N. Goufas, and S. C. A. Thomopoulos. Indoor localization with wireless sensor networks. 2010.

- F. K. Noble. Comparison of opencv's feature detectors and feature matchers. In *2016 23rd International Conference on Mechatronics and Machine Vision in Practice (M2VIP)*, pages 1–6, 2016. doi: 10.1109/M2VIP.2016.7827292.
- D. Sobel. A brief history of early navigation. *JOHNS HOPKINS APL TECHNICAL DIGEST*, 19, 1998.
- G. Spinoza Andreo, I. Dardavesis, M. de Jong, P. Kumar, M. Prihanggo, G. Triantafyllou, N. van der Vaart, and E. Verbree. Building rhythms: Reopening the workspace with indoor localisation. pages 106–116, 2021. URL <https://repository.tudelft.nl/islandora/object/uuid%3A060d104f-bce9-4608-9aa9-a73132317254?collection=education>.
- A. Vinay, D. Hebbar, S. Vinay, K. Balasubramanya Murthy, and N. Subramanyam. Two novel detector-descriptor based approaches for face recognition using sift and surf. *Procedia Computer Science*, 70:185–197, 12 2015. doi: 10.1016/j.procs.2015.10.070.
- O. Willems. Exploring a pure landmark-based approach for indoor localisation. Master's thesis, 11 2017. URL <https://repository.tudelft.nl/islandora/object/uuid%3A6332755b-72ea-4a74-a781-5cb3f951de67?collection=education>.
- L. Yang and M. Worboys. Similarities and differences between outdoor and indoor space from the perspective of navigation. 01 2011.
- Q.-Y. Zhou, J. Park, and V. Koltun. Fast global registration. volume 9906, 10 2016. ISBN 978-3-319-46474-9. doi: 10.1007/978-3-319-46475-6_47.