Final report 2019

Methods for identification of free navigable space

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Introduction

The research within this project is a part of four-year (2018-2022) international project named iNous focusing on seamless indoor-outdoor navigation for emergency response. The project is funded by South Korea government and leaded by Pusan University, South Korea. The overall idea of the project is to develop a workflow for navigation for the purpose of disaster management system as illustrated below (Figure1):

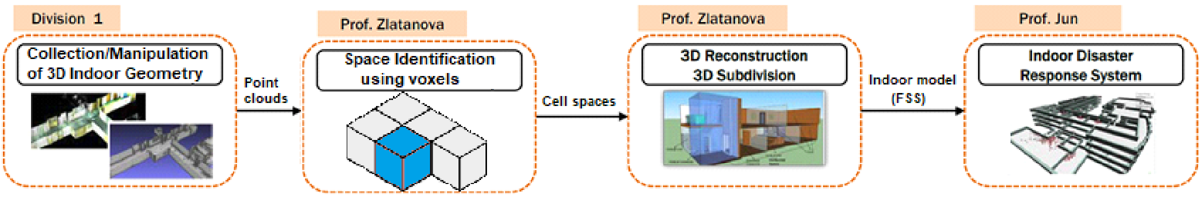


Figure 1. Workflow of the proposed Indoor disaster response system

In the second year of the project, the team of professor Zlatanova has concentrated on advancing the fee space identification from point clouds using voxels. The general scope of the research and developments have been defined as:

- Identification of strategies to progressively evaluate the level of semantic information of point clouds to be able to obtain a suitable input for indoor navigation in case of disaster management.
- Voxel classification and automatic free space identification based on it
- Space subdivision according to FSS framework with emphasis on type of objects and their functional spaces.
- Investigation of necessary semantic enrichment to properly generate the F-Spaces (functional).

The above objectives have been achieved by the following developments:

- algorithms for object classification of indoor point clouds into walls, floors, ceilings, air, stairs and undefined/furniture/obstacles
- algorithms for subtracting free navigable space.

Administrative information

In the specified period the following researchers were involved: Mitko Aleksandrov, Abdoulaye Diakité, Ben Gorte and Sisi Zlatanova. In this period no specific meetings were organised with the other teams on this specific topic although several discussions were carried out regarding the integration of FSS framework within IndoorGML 2.0.

Scientific project information

This year research has concentrated explicitly on developing a voxel-based workflow to derive 3D navigable spaces directly from point clouds. As discussed in (Diakite and Zlatanova, 2019), BIM and B-reps 3D representations can become very complex and lead to issues related to validity and intersections of solids or existence of tiny solids. In contract, voxels allow for a unified and flexible, yet relatively simple representation, which is favourable for 3D spatial analysis such as 3D navigation (fly, drive, walk). Voxel approaches have been also increasingly used for processing of point clouds in different context for 3D reconstruction (Poux and Billen, 2019; Huang et al 2019) or 3D navigation (Li et al 2018, Xiong et al 2016, Kitamura et al 1995).

Identification of strategies to progressively evaluate the level of semantic information of point clouds.

In this project period, we have considered two types of point clouds: 1) those that scanner position and the set of points collected from a station is known and 2) those that do not have such information because it has been either not collected or lost in the co-registration process. Scans created with Zeb Revo (having x,y,z trajectory and time of point collection) are example of point clouds that belong to the first category. The benefit of such information is that filtering of dynamic objects is a straightforward operation (Staats et al 2018). The availability of trajectory supports greatly the detection of doors, which is otherwise complicated (Nikoohemat et al 2019, Staats et al 2018).

We have voxelised point clouds scan by scan, i.e. before the co-registration, while assuming the scanner position is known. The approach can be summarised as follows: 1) create a voxel space for the area of the entire scanned area, 2) compute for each scan which voxels are traverse by each beam from the scanner until a surface is 'hit'. These are voxels are tagged as 'transparent'. Voxels that have a value (because of reaching a surface) are called 'hard'. All voxels that are not processed, because no beam is going through, are tagged as 'unknown' (Figure 2).

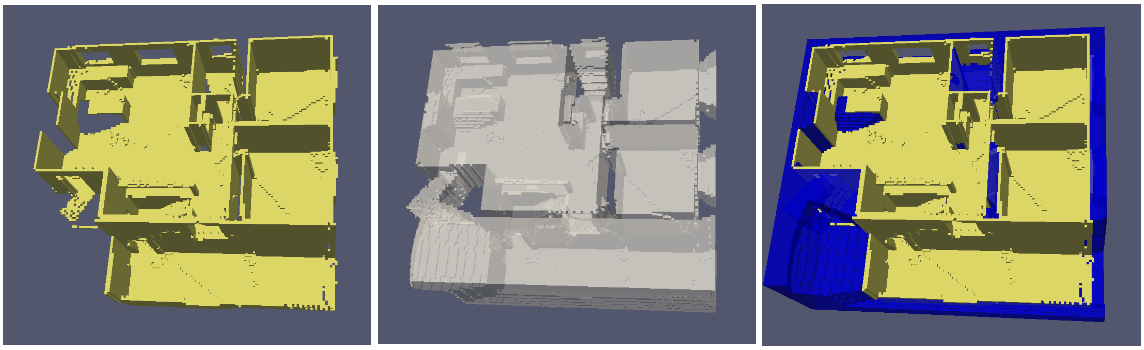


Figure 2: Reconstructed voxel model with three classes. Left: hard, centre: transparent, right: hard + unknown (Gorte at al 2019)

This approach allows to more accurately estimate which voxels (parts of the building) are secure to move through. Voxels tagged as 'unknown' are not included in the navigation as they have been occluded, hence there is no information is available if these areas are navigable. They might be but also might be not, therefore, better to be excluded from the navigable space. The navigable area in the used test building is illustrated in Figure 3. If a decision must be taken if the occluded spaces are navigable, then additional scanning has to be carried out to cover those spaces.

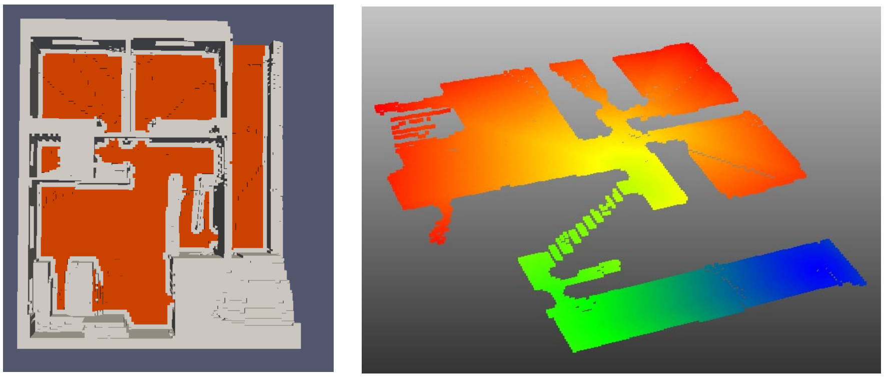


Figure 3:Navigable floorspace and distances to exit point in reconstructed model from pointclouds (Gorte et al 2010)

This approach can be used as a first estimation for progressive evaluation of the sematic information needed for navigation. As illustrated, at this first step, three classes are defined ‘transparent’, ‘hard’ and ‘unknown’. The ‘transparent’ voxels are to be utilised for navigation only. Consequent specialisations can be made for ‘walking’ mode by estimating only ‘transparent’ voxels above the horizontally (within certain threshold to include stairs) connected ‘hard’ voxels.

Voxel classification and automatic free space identification

The next step is to provide more semantic information, which requires further voxel classification of the ‘hard’ voxels. Within this project, another study was initiated to classify voxels into ‘floor’ (surfaces including flat areas and ramps), ‘ceiling’ (surfaces above floors and furniture), ‘wall’ (surfaces connecting floors and ceilings and considering building exteriors), ‘partial wall’ (either starting from floors or ceilings), ‘stair’ (areas with a specific pattern) and ‘door’ (starting from floors and matching with the position of walls). These investigations are on-going. The developments are intended to be integrated in Unity3D to facilitate the developments by employing the available Unity3D navigation tools. For example, Unity 3D has routines for estimating walkable area, considering the 3D model. The voxel classification methodology is as follows:

1. Creating voxels model from a point cloud
2. Identifying horizontal and vertical voxels
3. Estimating walkable connected horizontal surfaces, which includes flat surfaces and ramps
4. Estimating floors and ceilings
5. Classification of stair voxels based on a specific pattern
6. Identifying vertical voxels that connect floors and ceilings
7. Using trajectories and vertical voxels to identify doors (in case of scanning with Zeb Revo)
8. Extracting spaces

Currently the steps 1 to 4 are implemented and tested. The model used for the tests consist of 56mil point clouds, captured with BLK360 leica. The intention is the same tests to be performed with scans obtained with Zeb Revo to use the trajectory (Figure 8), which facilitates the detection of doors (Nikoohemat et al 2019). Surfaces representing floors and ceilings are currently successfully identified (Figure 5).

Figure 4. Detected floors and ceilings (unity3D)

After identifying all flat surfaces with 1000 and more voxels, stair voxels are detected on the non-classified voxels. To detect each voxel that belongs to stairs surrounding voxels are considered taking 0.7x0.7x0.65 m box of voxels into account. The detected voxels are presented in Figure 6.

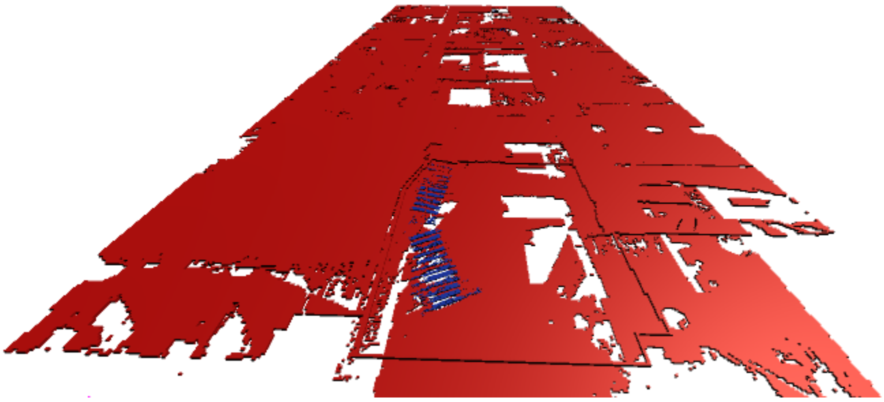


Figure 5. Voxel visualisation in Unity3D showing detected stairs

To detect voxels related to walls planes are fitted over the unclassified point clouds where planes that intersect with a floor and ceiling are kept. Based on the classified point clouds the corresponding voxels are classified as walls (Figure 6).

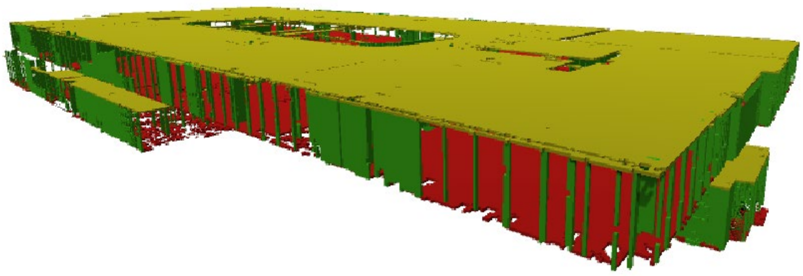


Figure 6. Voxel visualisation in Unity3D showing detected walls

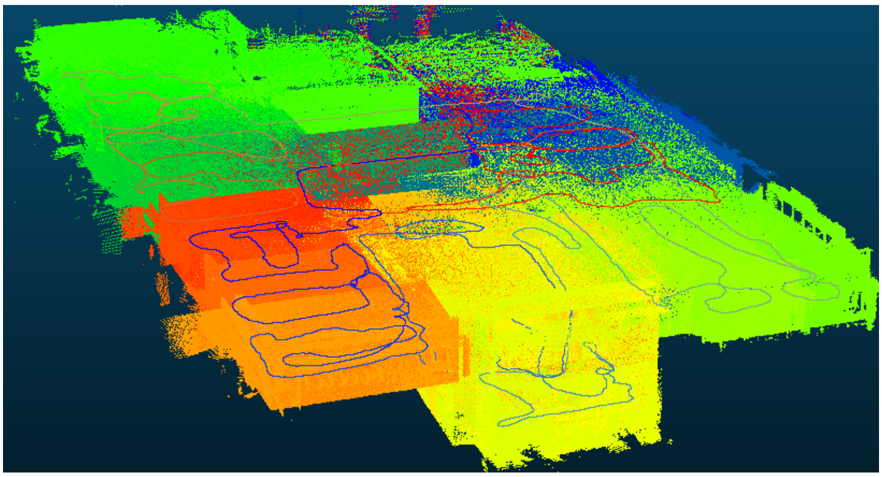


Figure 7: Indoor scanning using Zeb Revo and the collected trajectory.

As mentioned above, in the following work the use of scanning trajectory will be investigated for more accurate detection of features and doors. Once the objects are detected, spaces will be generated along with space subdivision to support indoor navigation. First experiments with space identification are shown in Figure *8*.

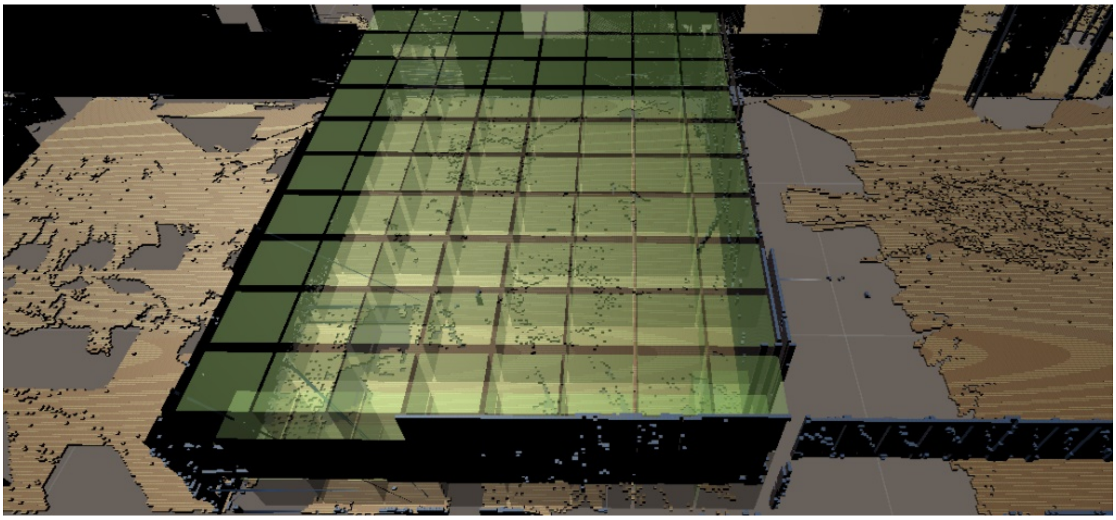


Figure 8. *Spaces identified on one room*

Space subdivision according to FSS framework with emphasis on type of objects and their functional spaces.

In the Flexible Space Subdivision (FSS) framework (Diakité and Zlatanova, 2018), the indoor environment is subdivided into three main subspaces depending on the elements that it contains:

- Object spaces (O-Spaces) which encapsulate the physical objects (static and semi-mobile features)
- Functional spaces (F-Spaces) which delineate the space needed by objects in O-Spaces to operate or temporary static activities of mobile features (e.g. people gathering for a chat in the corridor, etc.).
- Remaining free spaces (R-Spaces) which are the spaces left to be considered for a higher likelihood of obstacle-free navigation paths.

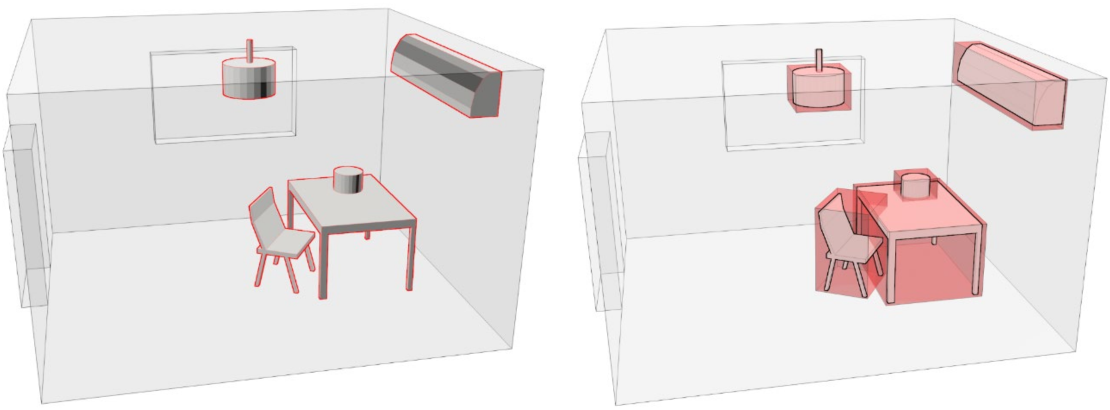


Figure 9: Complex O-Space (in red) extraction (left). Simplified O-Space extraction (right).

The process to extract R-Spaces from a BIM (3D vector model) have been already experimented previously. The common approach for this purpose is to first compute the O-Spaces and F-Spaces (optional) and subtract the later from the initial spaces through Boolean operations. However, because of the complex shapes of the furnishing elements of a 3D model, Boolean operations are getting very complex and prone to software crashes.

To make the process easier to compute, the shapes of the furniture are simplified using axis-aligned or oriented bounding boxes (AABB or OBB). Figure 9 illustrates the two possibilities, with the left option leading to complex Boolean operations between the containing room and the contained objects, while the right option leads to simplified O-Spaces.

The problem with this approach, as specified in (Diakité and Zlatanova, 2018), leads also to loss of free space that are encompassed in the simplified O-Spaces, and therefore wrongly considered as occupied. We believe that voxel representation is a way to overcome both the limitation of error prone processing and loss of free space.

We therefore carried out experiments on the extraction of R-Spaces from voxel models of indoor spaces. The process is similar to the one with BIM models (vector), in the sense that the O-Spaces and F-Spaces are first determined, and finally subtracted from the room spaces. For the purpose of the experiments we worked on a voxelised BIM model to directly benefit from the semantic information.

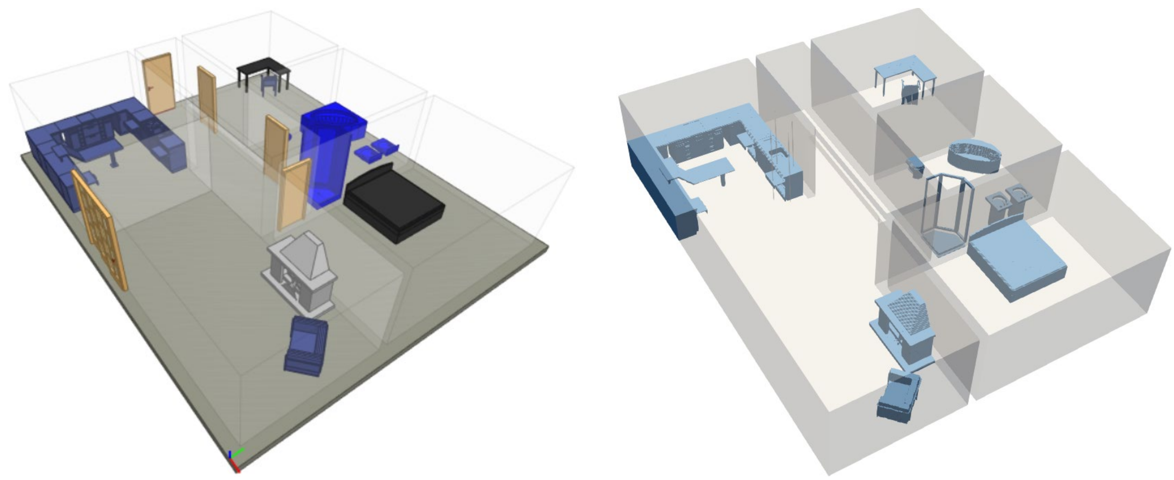


Figure 10: Spaces and furniture from a BIM model (left). Voxelized BIM model (right)

Figure 10 illustrates the voxelization of a BIM model (left) which led to a voxel model where furnishing elements are differentiable from the rest of the space. This naturally makes the extraction of the finest R-Space very straightforward as illustrated in Figure 11:

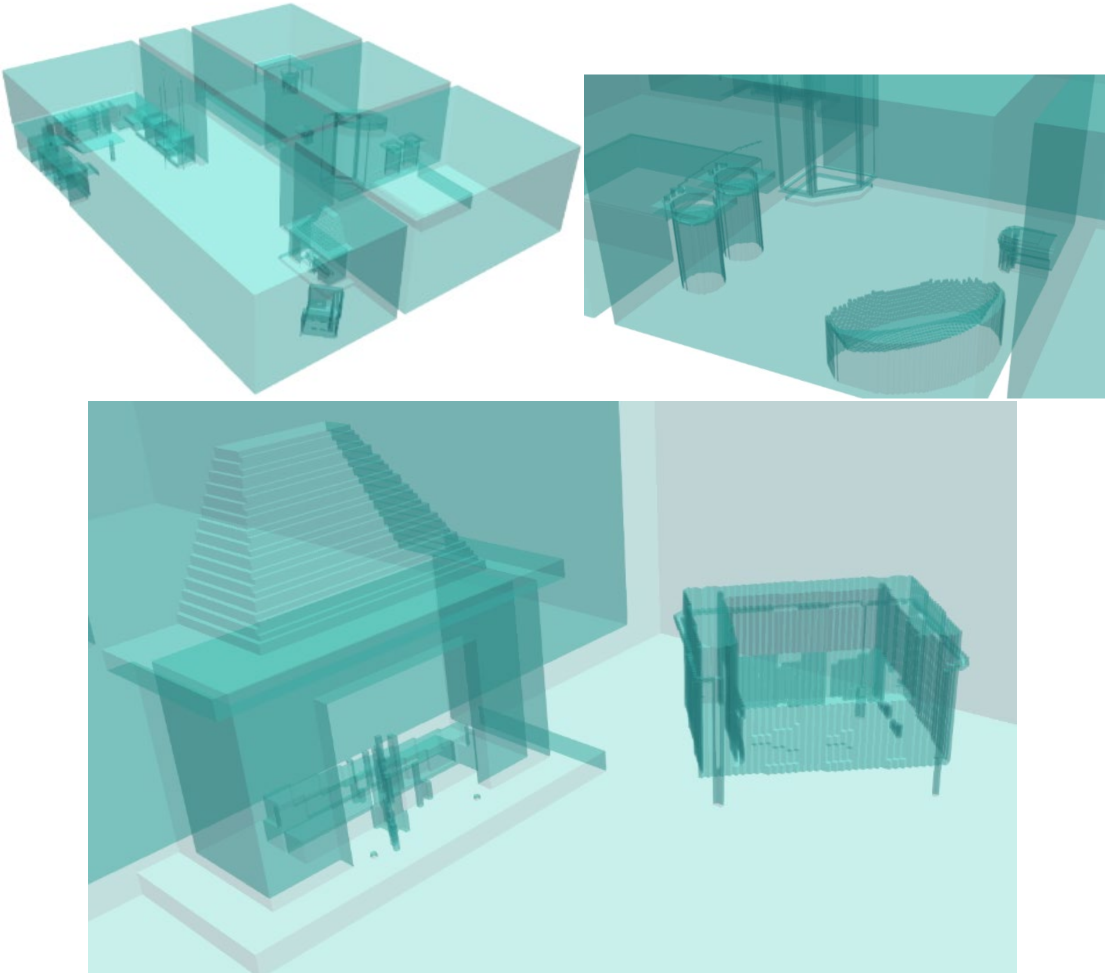


Figure 11: Furniture space directly subtracted from the indoor space.

The finest R-Spaces shown in Figure 11 corresponds to the direct subtraction of the furniture from the actual indoor spaces. This is the actual free space of the room when F-Spaces are not considered. Such operation is made easy by the advantageous structure of voxel allowing to directly identify and isolate the 'cubes' without a furniture value. It is also visible that the boundaries of the spaces are smoother compared to those of some furnishing elements, because the former are axis-aligned while the latter are not.

Figure 10 demonstrate the replicability of the full BIM FSS process on a voxel model. Similar O-Space (red volumes) than with a BIM model were created to add on top them a rough estimation of their corresponding F-Spaces (volumes in yellow). But now that finer O-Spaces of the furniture can be obtained, we can think of different processes to represent the F-Spaces, such as a direct dilation of the objects through a region growing process with some criteria that are yet to be defined. In fact, we still need to find a way to precisely identify the F-Spaces of indoor objects on the basis of their semantic rather than their geometry solely. Such investigation is discussed in the next section.

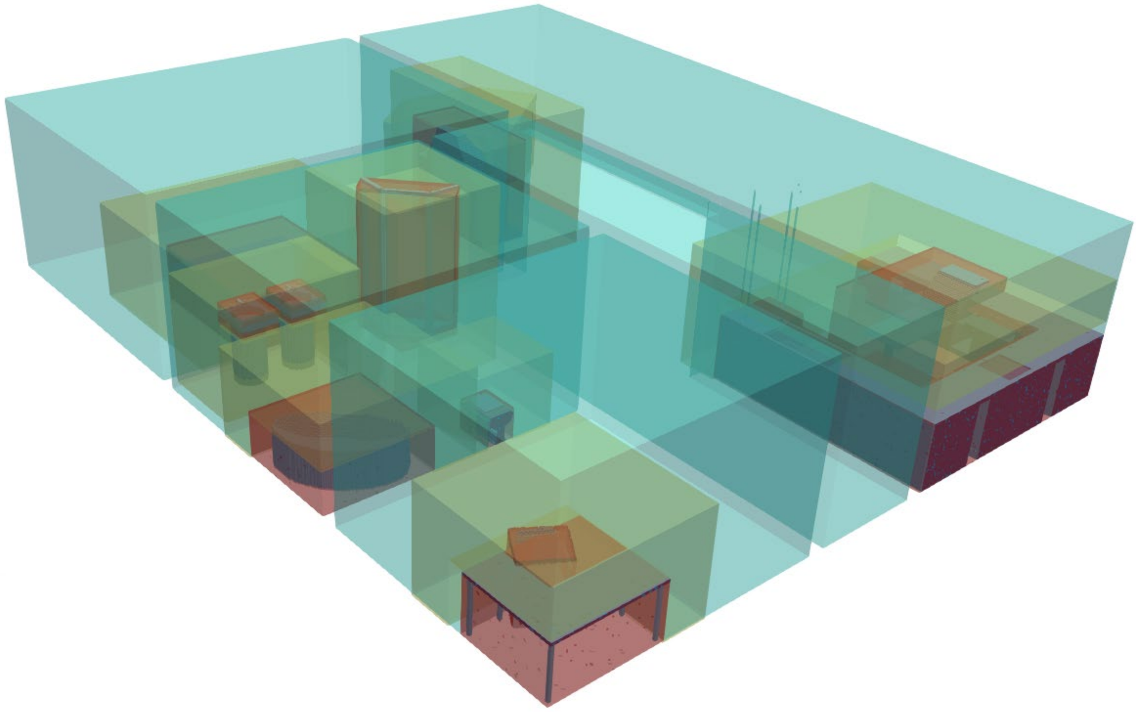


Figure 12: Full FSS process using O-Spaces as boxes, similarly to BIM models

Investigation of necessary semantic enrichment to properly generate the F-Spaces (functional).

We present here the initial findings of the investigations related to a better understanding of functional spaces. Our goal is to ultimately elaborate a method to automatically derive F-Spaces from 3D models of indoor objects. For this purpose, we explored fields such as spatial information theory, human-robot interactions, anthropology, cognitive and social sciences, seeking for means to estimate the spatial parameters describing the functional spaces.

The notion of functional space related to indoor objects has been discussed in the literature for several decades now. One of the most prominent contribution in that sense is the book of Ernst Neufert and Neufert 2012), which was first published back in 1936. Mostly oriented towards architectural design, the book presented an extensively detailed work about dimensional and spatial planning information relating to most human activities. On the basis of body measurements (mostly based on American and European data), the author explored all kind of space requirement to allow designs suitable to a proper use of objects as well as proper human activities in general, including activities for disabled people (Imre, 200).

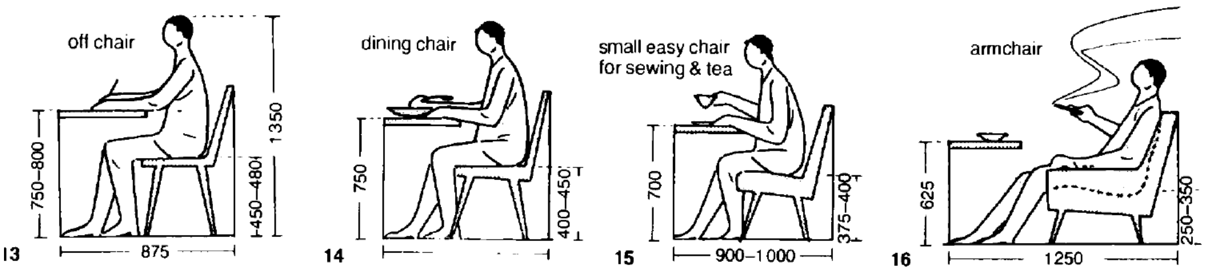


Figure 13: Example of potential functional dimensions of chairs in use by a person (source: Neufert and Neufert 2012).

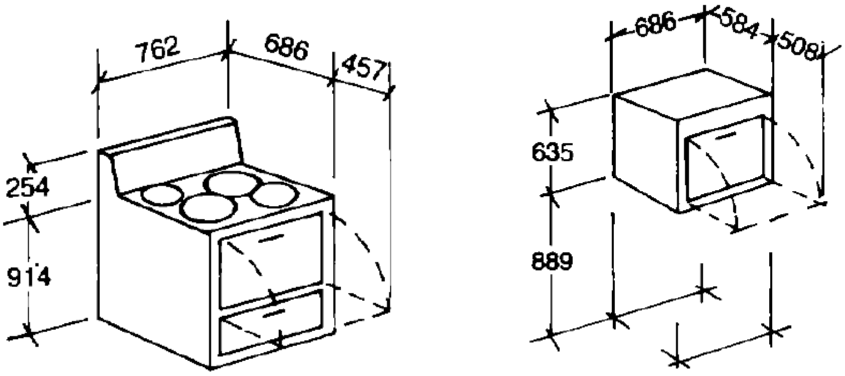


Figure 14: Example of kitchen appliances with their dimensions in functional and static conditions (source: Neufert and Neufert 2012).

Figure 13 illustrates dimensions that may be involved in the use of chairs and tables by humans. The space around the chairs and tables related to their functional roles seems to be indicated intrinsically by their shapes which determine where one can sit for example. Figure 14 shows spaces induce by the functional design of specific furniture. We can see that the dimensions of the objects when used can involve bigger dimensions that the one of the people using them. This information seems hard to capture in a static 3D model, solely on the basis of geometry. Storing it as a semantic information may be more convenient.

While this work of the Neufert brothers provides an extensive list of specific objects related to architectural environment (e.g. furniture of houses, hospitals, office buildings, etc.), with their specific dimensions, it does not provide means to automatically derive the functional space of a randomly given object. It can however help to set predefined spaces in a spatial model to account for functional spaces.

Another prominent contribution comes from the anthropologist Edward T. Hall who introduced the notion of proxemics in 1966 (Hall, 1966). The author defines the term proxemics as the interrelated observations and theories of people's use of space as a specialized elaboration of culture. He explored, among other effects, the invisible spatial boundaries that people unconsciously set in their interactions. This led to an entire new field of research where the personal space of people occupies a central place (Sommer, 1969, Lloyd, 2009), notably in the human-robot (Nakauchi and Simmons, 2002; Lindner and Eschenbach, 2011, Mumm and Mutlu, 2011) and human-media interaction fields (Vogel and Balakrishnan, 2004, Greenberg et al 2011). The notion of proxemics constitutes a relevant feature to consider in navigation as well (Krūminaitė et al 2014, Rios-Martinez et al 2015). More specifically, the link is made between the human personal space needs and the functions of objects, suggesting that the personal space of a person using or operating on an object affects the way others people behave around the same object (Junestrand et al 2001) . However, despite the estimations of the sizes of the virtual spaces provided by Hall, which characterize human proxemics, there is lack of representation of that notion that can support applications such as indoor navigation.

In parallel to those works and closer to our, few approaches have discussed the consideration of functional spaces of indoor objects in a spatial model for indoor navigation. In (Afyouni et al 2010), the authors introduced a 2D gridded and multi-layered model in which the presence of the furniture can be considered as well as their functional space. The latter is limited to the boundaries of the furniture's projection on the 2D Grid delimit the zone of interaction with it. More advanced notions of functional spaces are considered in (Zlatanova et al 2013), where the function is not necessarily related to resources (indoor objects) but can simply be the purpose of a space unit. Unlike other researches where the function of the spaces is limited to their general classification (e.g. room, office, etc.) (Richter et al 2009), the authors in (Zlatanova et al 2013) also considered the concept of finer 3D space subdivision in order to make the consideration of functional micro-spaces possible. However, only the idea is discussed, and no practical support were provided. In (Krūminaitė et al 2014), the authors considered the notions of proxemics to encapsulate human navigation behaviour in their spatial model. An estimation of functional spaces is provided on the basis of 2D plans and several other criteria (attractiveness, centrality, etc.). But the 2D abstraction oversimplified the environments and the level of subdivision did not allow optimal path computation.

Figure 15: Example of proxemics related to urban features and their inferred (a) or direct (b) functions. (source: Rios-Martinez et al., 2015)

Figure 15 shows two examples of functional spaces related to urban feature. In Figure 13 (a), the nature of the object induces an activity space in front of it, making it inconvenient for somebody to walk into that space while somebody else is using it (e.g. for a picture). Figure 15 (b) illustrates the direct functional space required for anybody to read information printed on the board, making potentially an inconvenient space to stand for waiting a bus.

Considering the outcomes and limitations of all those works, the geometry and semantic of a 3D model of a furniture may be enough to deduce a functional space of reasonable size and orientation. Our next step will therefore be the design a method that will determine the proper parameters of the F-Spaces on the basis of the indoor object's structures and the proxemics of their users. We will emphasize on the geometric aspect of the F-Spaces such as their size and orientation in 3D, on the basis of the theories previously discussed.

Other related topics

Within this project two other related topics were investigated. Substantial work was completed within IndoorGML 2.0 as well as extending the space-based concept to outdoor. Two critical papers for creating outdoor spaces where published.

IndoorGML 2.0

Several discussions within the team resulted in further extending IndoorGML standard with attributes and code lists. The developments were present at OGC TC meetings.

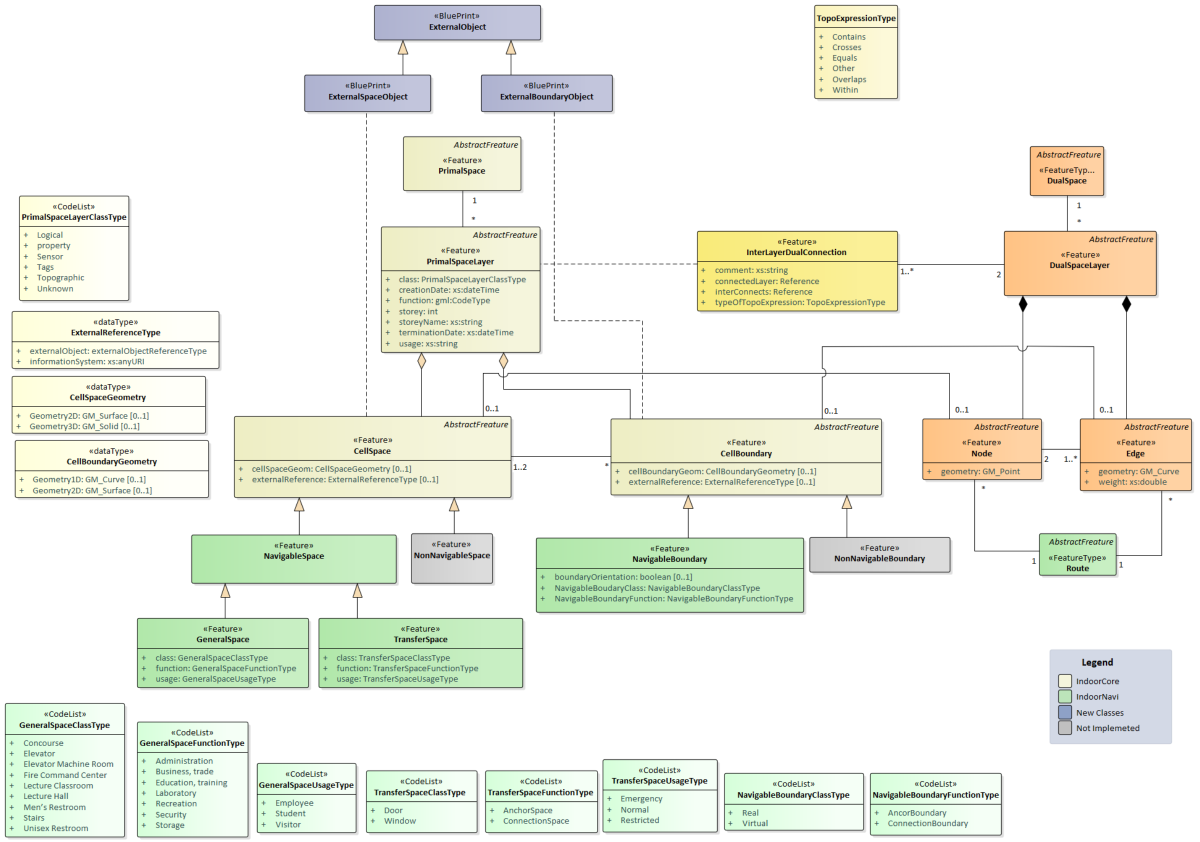


Figure 16: Current version of IndoorGML 2.0

Newly emerged topic: outdoor space subdivision

As discussed last year, the research on indoor-outdoor space subdivision progressed further with defining a generic framework for defining/classifying spaces into indoor, semi-indoor, semi-outdoor and outdoor (Yan et al 2019). These spaces are used to derive unified indoor-outdoor network. This research has confirmed that FSS strategy can seamlessly be applied for any application indoor or outdoor. Since the semi-indoor, semi-outdoor and outdoor spaces are open from above or aside, procedures for space reconstitution were developed (Yan at al 2019). A series of tests were conducted on a 3D model of the UNSW campus (Figure 17) and the corresponding automatically computed network using Poincare Duality (Figure 18).

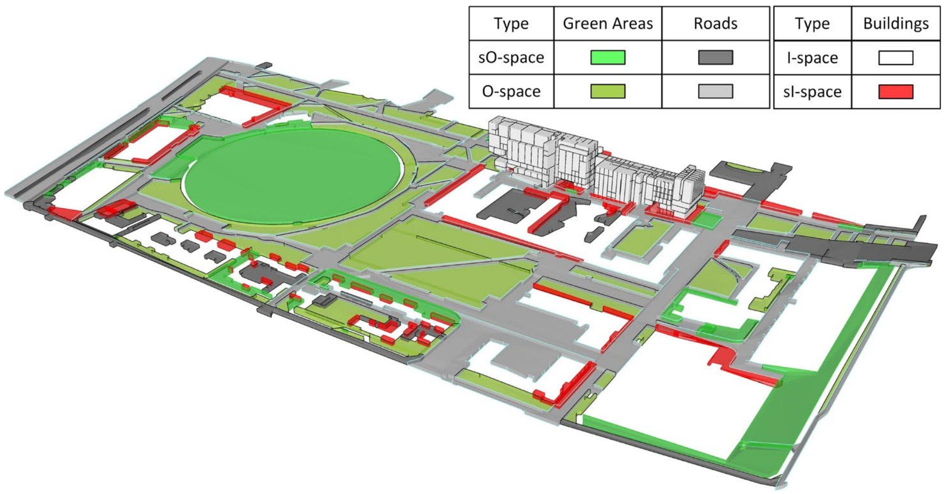


Figure 17: Spaces defined at the UNSW campus

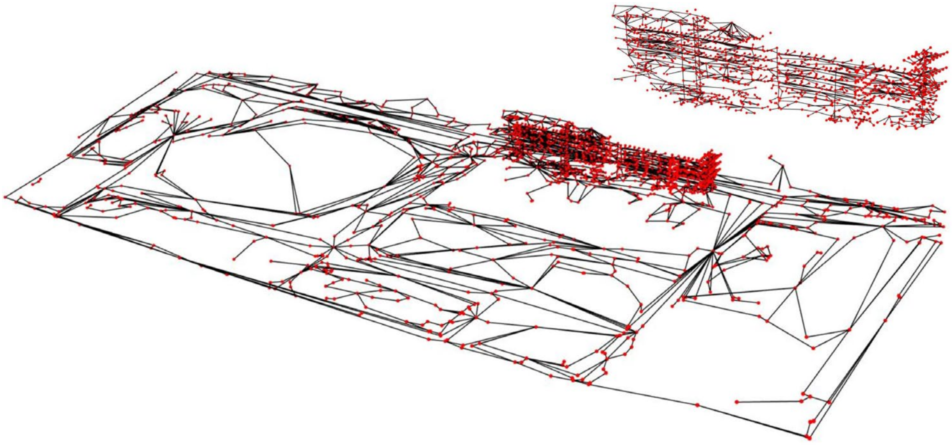
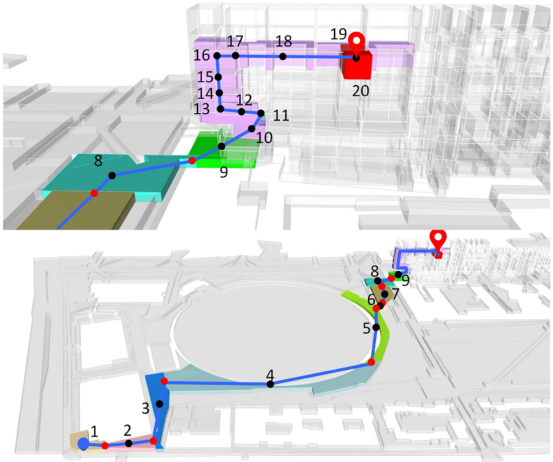


Figure 18: Seamless space-based indoor/outdoor network



No.	Name	closure			SpaceType
		C^T	C^S	C^B	
1	road80	0	0.99	1	sO-space
2	sI19	1	0.71	1	sI-space
3	road71	0	0.08	1	O-space
4	greenArea36	0	0.49	1	O-space
5	greenArea29	0	0.49	1	O-space
6	road33	0	0	1	O-space
7	greenArea44	0	0	1	O-space
8	road25	0	0.19	1	O-space
9	greenArea49	0	0.20	1	O-space
10	G032	1	1	1	I-space
11	MQ01	1	1	1	I-space
12	MQ02	1	1	1	I-space
13	1Q01	1	1	1	I-space
14	2Q01	1	1	1	I-space
15	3Q01	1	1	1	I-space
16	4Q01	1	1	1	I-space
17	Door	1	1	1	I-space
18	4Q04	1	1	1	I-space
19	Door	1	1	1	I-space
20	4036	1	1	1	I-space

Figure 19: An example for seamless indoor/outdoor navigation.

Figure 19 illustrates an example of indoor/outdoor navigation.

Milestones

- Structuring of Indoor Information: completed voxel classification in two levels: 1) ‘transparent’, ‘hard’ and ‘unknow’ and 2) ‘partial wall’, ‘floor’, ‘ceiling’ and ‘stair’.
- Space subdivision according to FSS using voxels: R-space (free navigable space) and O-spaces completed. An investigation on the way to automatically identify F-space is completed.

Conclusions

The project continues according the plan with few small deviations on the conceptual part. A summary of the completed developments is given below:

- Processing of point clouds to voxels
- Algorithms for voxel classification
- Algorithms for voxel path navigation
- Algorithms identification of free navigable space (from point clouds and BIM models)
- Algorithms to create semi-indoor, semi-outdoor and outdoor spaces (vector-based)
- Algorithms for seamless path navigation (vector-based)
- And extended UML for IndoorGML 2.0

Publications within this project

Diakité, A, and S. Zlatanova, 2019, Valid Space description in BIM for 3D Indoor Navigation, Architecture and Design, ISBN13: 9781522573142, Chapter 25, pp. 688-706

Gorte, B., S. Zlatanova, and F. Fadli, 2019, Navigation in indoor voxel models, ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., IV-2/W5, 279-283, https://doi.org/10.5194/isprs-annals-IV-2-W5-279-2019, 2019

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