A Conceptual Digital Twin for 5G Indoor Navigation

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***Abstract*—With the introduction of practices from Industry 4.0 in various Architecture, Engineering, Construction, Owner and Occupant (AECOO) sectors, especially in Facilities Management (FM), new requirements concerning integration of digital data sources arise with prominence. Particularly with the increased use of the Digital Twin (DT) paradigm, the need to capture, store, process and present various data concerning the current and predicted states of the built environment becomes paramount. A conceptual and prototypical system design, focusing on integration, processing, analysis and visualization of data related to indoor navigation within modern buildings, is presented and discussed. Approaches for processing and presentation of key data sources, particularly indoor point clouds and as-is Building Information Modeling (BIM) data, combined with simulated 5G signal as localization approximation, are presented and discussed. A particular focus is placed on leveraging the Service-Oriented Architectures and Systems (SOA/SOS) paradigm for implementation of complex systems for meeting integration requirements of such diverse data sources. Finally, we discuss how such approaches can benefit from current and predicted use of 5G technologies, and provide experimental results from a case study conducted within a modern university campus building. The presented case study results demonstrate the feasibility of our approach, and provides a framework for future expansion, integration and evaluation with planned 5G infrastructure.**

***Index Terms*—Point Clouds; BIM; Service Oriented Computing; Localization; 5G Simulation**

I. INTRODUCTION

Current advancements in adaptation of Industry 4.0 practices for Architecture, Engineering, Construction, Owner and Occupant (AECOO) stakeholders, particularly in the realm of Facility Management (FM), have created a paucity for the research and development of integration strategies for digital data sources [1]. Such data sources may include as-designed/built/as-is Computer-Aided Design (CAD) and Building Information Modeling (BIM) data, digital and digitized FM documents as well as historical or current sensor data - all pertaining to the past, present and future operational state of a building [2]. With the current standardization of 5G technology, additional data sources captured via 5G infrastructure should be available for assessing the current state of the built environment, for, e.g., indoor navigation [3] or FM within a Smart Building context [4]. The fusion of all these data sources into a dynamic representation is based on the currently promoted Digital Twin (DT) paradigm [5]. A DT is able to encapsulate and represent the physical state of an object as its cyberphysical counterpart [6]. The use of DTs has potential benefit for engagement of stakeholders through interactive visualization [7] and enables an up-to-date virtual representation of their facilities and related states and processes [8].

A. Problem Statement

The focus of this research is on indoor navigation based on the DT paradigm. The deployment and use of a DT requires access to various data sources related to the specific lifecycle stage of the building. For FM applications, historical and current data sources are needed in order to perform key analytics and generate results for furthering FM stakeholder engagement. Additionally, future states also need to be predicted. This poses three key problems:

1) The selection and analysis of required data used to represent the historical and current states of a building (e.g., existing BIM data).
2) The selection and analysis of required data used to generate predictions for future states of a building (e.g., signal and sensor data obtained from 5G infrastructure).
3) The combined analysis and representation of these data sources.

B. Research Contributions

To address these problems, we present an approach for integration, processing, analysis and visualization of key data sources for indoor environments. Our focus is on indoor localization and navigation tasks with a FM context (Fig. 1). An SOA for integration of such data for DT representations is presented and discussed. A prototypical implementation of key system components is tested using data from a real-life university building with a simulation for 5G-based localization. We also use synthetically generated point clouds, based on as-is BIM data, in order to test our point cloud processing and reconstruction methods. The fusion of historical, current and predicted data sources is then used to generate indoor navigation results, which are interactively visualized alongside existing BIM and FM data (e.g., 2D floor plans, 3D models and point clouds). The final output is presented as a web-based, interactive visualization aimed at engaging FM stakeholders for indoor routing and navigation tasks.

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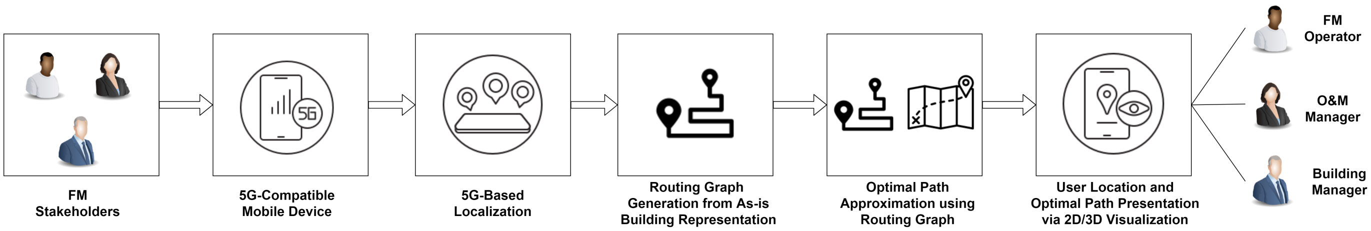

Fig. 1. The proposed approach of using 5G data and BIM data within a DT paradigm for indoor navigation and localization tasks related to FM.

II. Related Work

A. Requirements for Indoor Navigation Modeling

A key requirement of indoor navigation is the determination of navigable areas within the chosen representation (e.g., 2D floor plan, BIM, etc.). A navigable area is defined as a region in 2D or 3D space where an agent representing a user or an autonomous entity is able to move around - in order to get from one location to another. A common name for data structures used to represent such navigable areas are ”routing graphs” [9] or ”navigation meshes” [10]. The use of routing graphs is therefore a requirement for pedestrian indoor navigation, especially for approximation of optimal paths (e.g., using Dijkstra’s algorithm and its variants [11]). Existing BIM data and semantics (e.g., Industry Foundation Classes (IFC) schematics [12]) can be used in order to determine the geometric boundary constraints of areas that are navigable [13]. Methods for discretization of 3D space and approximation of topological derivatives using geometric computation principals also play an important role for generation of routing graphs [14] [15].

B. Capture and Representation of Indoor Environments

In AECOO applications, the use of point clouds enables the area-wise capture of intricate physical details of indoor and outdoor built environments, real-world objects and locations, with varying levels of visual fidelity [16]. Point clouds can be generated by using photogrammetric techniques and by laser scanning [17] [18]. In laser scanning, laser signals emitted by 3D scanners are used to capture the reality based on time of flight or phase shift methods [19]. For AECOO applications, in particular Operations & Maintenance (O&M) procedures within FM, the current state of the physical environment can be captured using point clouds and analyzed for further decision making [20].

The simulation of the laser scanning process can also be performed, known as ”synthetic data” generation, using as-designed/as-built or as-is 3D models of indoor environments as the main processing input [21]. The output of such a process is a point cloud with similar qualities as that of a physically captured point cloud, and can be used for various testing key processes (e.g., training machine and deep-learning models for semantic segmentation [22]).

Apart from manual generation of as-is and as-built BIMs, the application of the “Scan2BIM” process enables automated reconstruction of segmented point clouds to semantically-rich and higher-level geometric representations (e.g., as-is BIM data in the form of IFC models [23]). This can also include both 2D and 3D floor plan generation [24]. Since point clouds themselves are ambiguous, they need to be processed and enriched semantically in order to make them useful for visualization and analysis applications [25].

C. Localization Methods within the 5G Paradigm

The increased use of smartphones with integrated cost and energy efficient sensors for navigation and localization correspond to the ubiquitous positioning vision proposed by Park in [26]. Determining the optimal route to get between two points is often a bottleneck for FM tasks, and solving such a problem requires the approximation of the user’s current location within a building as well as the approximate location of the destination point. One key approach to solving this problem is based using autonomous localization methods - independent from any other infrastructure solution, e.g., WLAN or UWB networks, which need an app registration or a predefined label dataset [27]. However, such autonomous localization performance would be limited both in physics-based solutions [28] [29], or machine learning-based approaches [30] [31], due to the well known sensor drift and the absence of a realistic dataset respectively [27].

The current introduction and adaptation of 5G networks is of great interest for application of indoor localization within a BIM-based FM usage context [32]. The use of 5G infrastructure and technology could increase the accuracy of indoor navigation applications, and would therefore be useful to consider for FM-related tasks by providing benefits within a Smart Building context (e.g., stable and low-latency communication, multi-device support and use for data-heavy streaming applications such as Augmented and Virtual Reality (AR/VR) [4]). Since the 5G technologies would be available to the vast majority of the population, it can be expected to be a staple technology to benefit indoor navigation, and capable of solving current open localization challenges in the built environment [27]. Variants of such 5G infrastructure (e.g., using a specialized 5G network that uses slightly different frequencies than a ’normal’ network), can also provide similar benefits.

D. Service-Oriented Architectures and Systems

The use of the DT paradigm further places demand on availability of historical and current digital information for a given building [33]. The use of service-oriented computing and system architecture enables the design and deployment of complex software components and services, which are capable of meeting the requirements of accessing, storing and processing versatile data sources - along with the benefit of hardware decoupling between the server and the client systems [34].

A particular advantage of using SOA when implementing SOS-based FM software systems (e.g., CAFM, BAS and IWMSs [35]), is the processing and streaming of specific results related to FM tasks for a given building (i.e., visualizations of recent spatial changes of office furniture and/or equipment, occupancy levels, environmental sensor data, approximations for indoor localization,etc. [36]). Once received, these results can be presented on any connected client devices of stakeholders running, e.g., a compatible web-browser on a commodity mobile device [37].

III. Approach

The main paradigm for presentation, interaction and decision making is envisioned with the use of a DT. The type of data utilized by the DT would depend on its intended use case, but in most cases the data needs to represent the physical characteristics of the entity that is presented digitally. For FM-specific applications this would include as-is point clouds and their generated semantics, as-is BIM data, as well as any existing data pertaining to the current representation and operational status of a building (e.g., Mechanical, Electrical and Plumbing (MEP) plans and status reports, floor plans, as-built/as-designed BIM, current or historical sensor data, etc.). The fusion of these data sources when generating the required result of the user's computation tasks is the essence of the DT [38].

The Data Processing and Data Analytics components of such a DT system would be implemented as services that are run when a specific task is requested, and would process and stream the result of the task back to the user. Such an approach fits well with the use of service-oriented computation, and is the recommended approach for implementation of DTs for AEC applications [39]. All of the processes can be automated and/or simulated, and included as software components and services within a SOS implementation (Fig. 2).

a) Point Cloud Processing: The capture of the as-is physical state of indoor environments can be accomplished with the use of point clouds. The use of indoor laser scanning can produce point clouds representing intricate details and can provide useful base-data for further processing and semantic enrichment (Fig. 3) However, if the capture of point clouds is not possible or prohibited due to various factors, their capture can be simulated using existing 3D models of indoor environments as the main inputs. Using methods such as Monte Carlo point sampling [40], or complete LiDAR device simulation [41], synthetically generated point clouds can be used as data sources for experimental assessment of key processing, semantic enrichment and visualization methods.

Further processing of captured or generated point clouds commonly involves registration, sub-sampling, noise filtering and per-point normal vector computation. Such tasks can be automated within a point cloud processing pipeline, and implemented with an SOS [42]. Most point cloud data management is currently done at the file level and there are different file formats specifically used for storing point cloud data (e.g., LAS [43]). As point clouds can be very large, they cannot always be loaded completely into system memory. To enhance performance for accessing, analyzing and viewing point clouds, different spatial data structures such as octrees or k-d trees can be used [44].

b) Database Integration: For FM use where point clouds need to be generated frequently, storing and distributing thousands of separate point cloud files is not sufficient for basic point cloud data manipulation. Here, a Database Management System (DBMS) represents an alternative that is easier to operate and scalable [45]. A relational or non-relational DBMS can be used, with additional special spatial indexing operations, in order to quickly access point cloud representations of, e.g., entire floors or specific rooms of a building, for processing and analysis. This also allows for the integration of point clouds with additional static (e.g., IFC models [46]), and spatio-temporal data sources (e.g., collected or real-time sensor data [36]), using non-relational DBMS that can accommodate the changing representation specifications for smart building related data.

c) Semantic Enrichment of Point Clouds: While point clouds can be used to represent intricate details of indoor environments that can be interpreted by viewers with domain expertise, point clouds themselves do not contain any semantics by default. Therefore, the use of supervised and unsupervised machine and deep-learning algorithms is needed to add useful semantics to point clouds (e.g., prior to reconstruction to as-is BIM representations). Unsupervised methods include segmentation and clustering methods such as RANSAC, Region Growing, k-means and DBSCAN clustering [47] [48]. These methods attempt to group together points that share similar features (e.g., spatial position, color, normal vector direction, etc.) or fit to a geometric primitive (e.g., a hyperplane using variants of the Least Squares method).

Supervised methods include the use of learning models where examples of what the model should output is based on observations from existing data (i.e., *a posteriori* knowledge). This commonly includes the use of Convolutional Neural Networks (CNNs) that can classify 2D and 3D data (e.g., point clouds, images of point clouds and higher-level geometric representations, e.g., voxels) into user defined categories using a classification model trained on previous examples [49].

d) As-Is BIM and Routing Graph Data Generation: The generation of as-is BIM data is based on the detection of semantically segmented point clusters, from which the geometry is used to infer the dimensions of the element to be reconstructed, and the label is used to infer the semantic associated with the element, usually with association to an IFC specification at a given Level of Detail (LOD). Semantically

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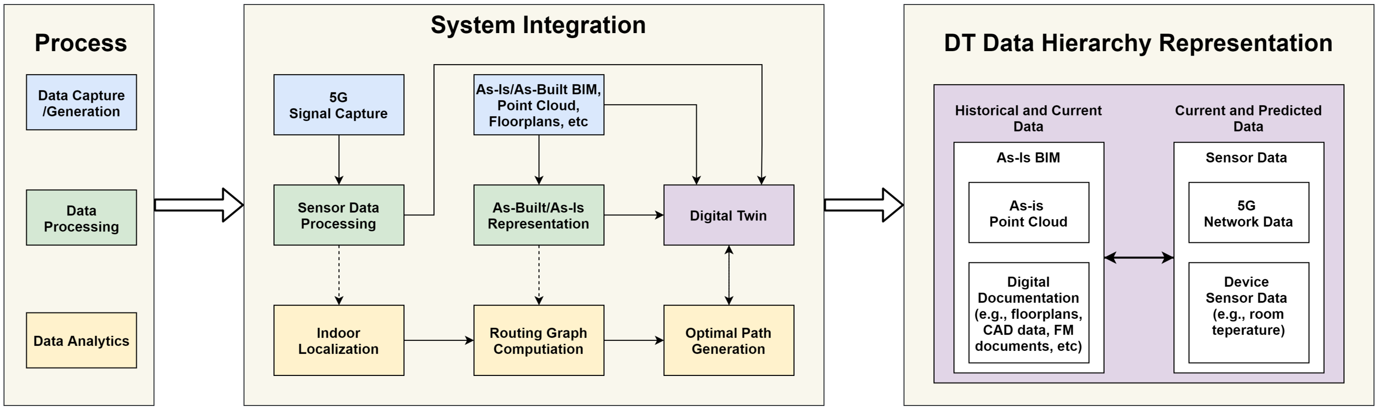

Fig. 2. High-level representation of key processes, system integration, data sources and hierarchy representation for the conceptual use of a DT for indoor navigation tasks.

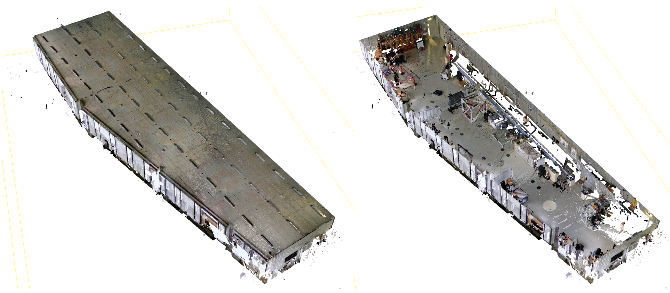

Fig. 3. An example of a point cloud of one of the areas in the university building presented in the case study, captured using indoor laser scanning and sub-sampled to 556 410 points.

segmented point clouds can also be used to generate 2D/3D floor plans. Such floor plans can either be 2D vector image data or 3D triangulated meshes.

For indoor navigation applications, besides geometric representations, an additional geometric data structure is needed to represent navigable areas. With a routing graph representation, the edges represent navigable paths, while the nodes are represented by vertices. Routing graphs and navigation meshes can be obtained both from 2D and 3D floor plan representations. For 2D floor plan representations, they are commonly generated using medial-axis approximation methods [50], while for 3D floor plans they can be derived either from the triangulated mesh topology representing the floor area, or from the semantics derived from the IFC elements representing navigable and room boundary elements [13].

e) 5G Simulation, Processing and Localization Methods: For navigation applications, the use of localization methods is required for approximating the user's position in relation to their surroundings. In order to approximate the user's initial location, different absolute positioning algorithms (e.g., triangulation, trilateration and multilateration), can be used to determine the approximate location of the user [28]. Additionally, the user's current location can be estimated based on the fusion of the maps information, routing graphs, the absolute positions and the received sensor data readings by using different state estimation algorithms (e.g., Monte Carlo Particle Filtering or Extended Kalman Filtering) [29].

With the availability of precise localization offered by the coming releases of 5G networks, user's mobile devices can capture and process localization data, as well as provide additional sensor data output such as barometer readings (i.e., used to measure height changes). The proposed approach relies on such input data in order to determine the user's approximate location, and can further make use of IoT and Smart Building paradigms by utilizing environmental sensor sources (e.g., RFID and NFC tags in building rooms [51]).

f) Representation and Interactive Visualization: Engagement with stakeholders through visualization plays an important role in furthering understanding amongst all levels of domain expertise. The use of interactive visualization, particularly for FM tasks, is crucial for enabling the visual representation and interpretation of key built environment elements and processes (e.g., planned renovations, item inventory, emergency route planning, etc.) [20]. The use of interactive visualization can greatly benefit indoor navigation tasks, where there is a need to combine as-is representations of buildings (either as 2D floor plans and/or with combined/exclusive 3D representations [52]). In such cases, stakeholders can use the as-is representation to interactively view their current location within the building, and use generated optimal paths for navigation between set markers.

Visualization of key data sources is enabled using real-time 3D rendering, mainly using existing game engines (e.g., Unity [53]) or Web3D frameworks (e.g., Three.js [54]). If dealing with complex data sources (e.g., visually complex 3D models or point clouds), out-of-core and SOS rendering methods can be utilized [44]. The representation of the as-is built environment, either as a raw or semantically enriched point cloud, or as an reconstructed higher-level geometric representation with associated semantics (e.g., 2D/3D floor plans, IFC models, etc.), enables stakeholders to visualize the environment as they may see it in real life, but with additional visualization metaphors and idioms [55].

IV. CASE STUDY

A. Overview

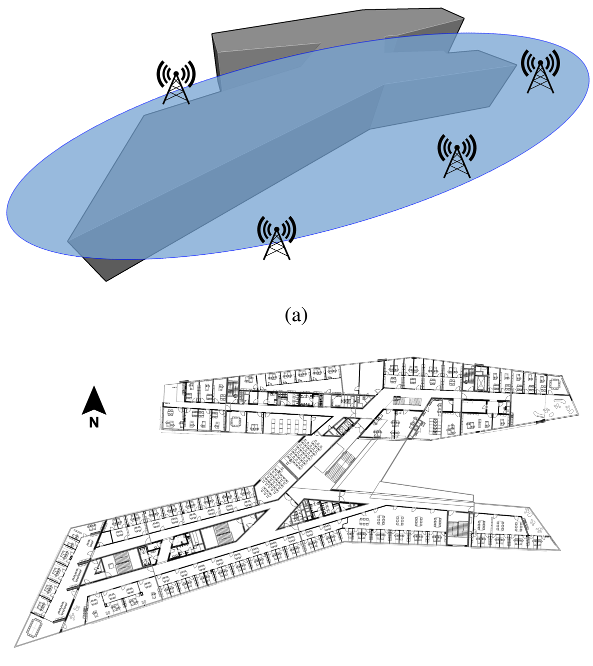

Fig. 4. (a) The planned 5G antenna locations around the perimeter of the building used in the case study. (b) An example of the architectural floor plan of one of the main floors of the university building.

A 5G Non-Standalone (5G NSA) campus network and an additional experimental system will be realized at the presented university building location between Q3 2021 and Q1 2022. Applications from the field of indoor navigation will be tested there and will serve research purposes. The planned campus network will consist of four outdoor antennas arranged around the building (Fig. 4(a)). Currently this process is in the planning stages, and more specific implementation details will be determined in the near future. For the planned outdoor and indoor network, the use of private frequencies in band B43/N78 (3.7–3.8 GHz) with a Long-Term Evolution (LTE) anchor band is planned. The aim is to set up, operate and use the networks as realistically as possible, as they can subsequently be set up and used as productive systems at other locations. The project will also set up a second experimental network. This network will work with frequencies in the range of 26 GHz–78 GHz to achieve even higher accuracy for the estimation of the position. In addition to this and for further research purposes, indoor units will also be provided on two floors of the building. In this way, the project will create different scenarios for testing indoor navigation.

Prior to the implementation of this infrastructure, it was decided to test key components in terms of their feasibility to generate and process data required for representation for indoor localization and navigation. As the 5G infrastructure is still absent, it was decided to simulate partially the key missing aspects, in order to validate the feasibility claim of the DT paradigm, presented approach and prototypical SOA and SOS. We therefore simulate the indoor 5G network for the presented case study, using the basic cellular positioning measurements and algorithms. The reference points are used as the basis of such a simulation.

We particularly focus on the aspect of localization and navigation within a given floor space of the main university building (Fig. 4(b)). Using an as-is BIM data of the fourth floor area of the university building, we simulate the laser scanning, positions and signals of 5G antennas. We use this simulated 5G data to approximate the coordinates of the user as they are virtually navigating the indoor area. For the implemented case study, we present and discuss key SOS components for processing data sources for generating indoor navigation results that are presented to the user through interactive visualization. The virtual navigation and user interaction is enabled through a web-based application, while processing and analysis of data sources is implemented server-side as SOS components.

B. Prototypical System Design and Implementation

We present a conceptual SOA, with key processes implemented as SOS software components and a Web3D-based client application (Fig. 5). The Web3D-based client is able to display either a point cloud or as-is BIM representation of an indoor environment, the user's simulated and approximated position. The generated optimal path between the user's current location and a defined point anywhere on the as-is BIM/point cloud can also be visualized. This optimal path, the as-is BIM/point cloud and the user's approximate location are displayed to the user interactively - enabling the user to inspect the each of the 3D scene elements from different views.

In terms of the back-end implementation, the prototype application is able to process point cloud data and create an initial version of the 2D floor plan. We also make use of a manually generated IFC model at LOD 300 of the same floor plan area, in order to provide additional data source for analysis and visualization of indoor navigation tasks. Additionally, the simulated 5G signal and localization estimates are implemented, along with a software component for optimal path generation using routing graphs generated from either the 2D floor plan or the 3D as-is BIM. The access to metadata related to the 2D floor plan, BIM, point cloud and FM data is provided via a DBMS also running on the server, while the actual files are stored on the same server within a specified directory structure. For the back-end systems, PostgreSQL DMBS is used as object-relational DBMS. With its spatial database extension PostGIS [56], it provides support for georeferenced objects that enable location queries (e.g., for processing of 2D floor plan representations). The simulated 5G capture works based on the reference points and can be combined with physics-based sensor fusion (i.e., pedestrian dead reckoning). The accuracy of such simulation can be defined by considering the current 3GPP release specification [57]. In other words, having the truth trajectory leads to a 5G simulation data by giving them some noise

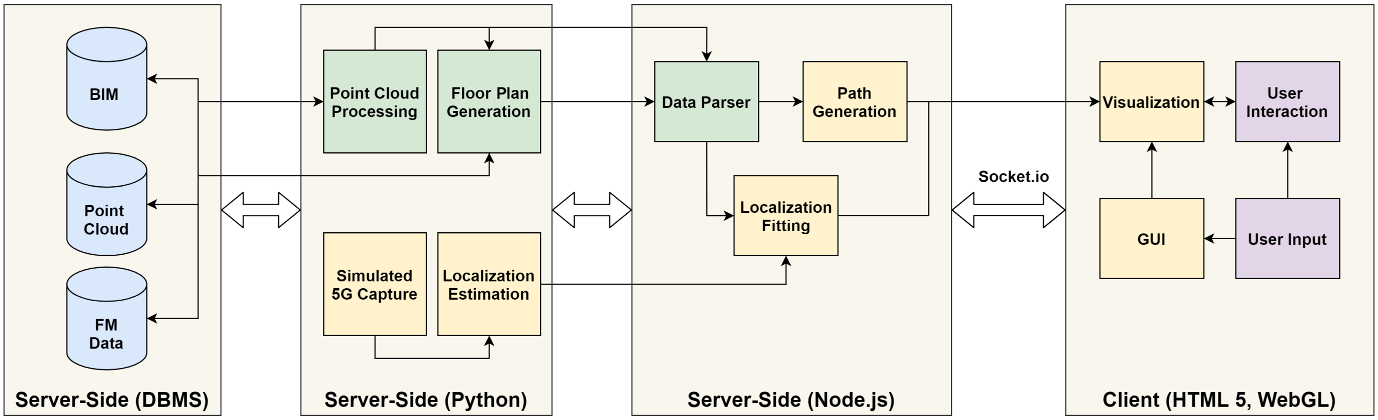

Fig. 5. A high-level system design for the presented prototype application, with key SOS components implemented server-side.

and timestamp. The time stamps are estimated using manual video analysis. The simulated points can be the basis for measurement estimation considering the pre-defined random noises. For instance, using the distance between one position and the antennas, measurement like time of arrival can be simulated.

The server-side software components are primarily implemented in JavaScript in Node.js [58], with additional components implemented in Python 3.6 and called as server-side scripts by a Node.js extension. Psycopg [59] can be used to connect to the database server and communicate with Python scripts. This DB API 2.0 compliant PostgreSQL [60] database adapter is designed for multi-threaded applications and maintains its own connection pool. It is mostly implemented in the C language, thus being efficient. Communication between the client and server is enabled via the Socket.IO [61] library. The client-side application is implemented in HTML5 [62], and uses the WebGL-based Three.js [54] rendering framework to facilitate real-time 3D viewing of the generated results.

V. Implementation and Results

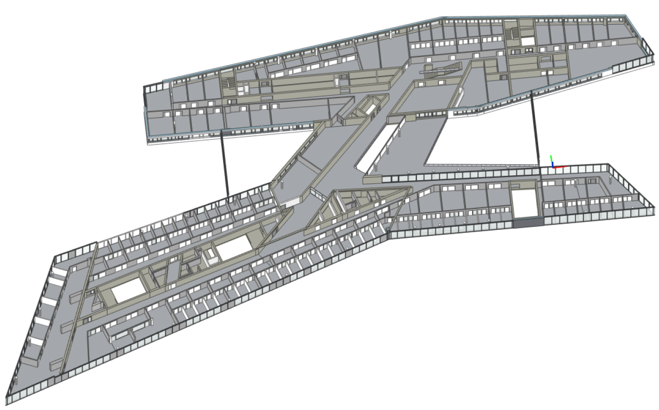

Fig. 6. The as-is BIM of the university building area used in the case study.

We present experimental results obtained from each of the key SOS component implementations, using mostly simulated data related to a functional office floor space within a modern university building (Fig. 6). We present and discuss processing of point cloud representations of this environment (generated synthetically from the as-is BIM), and the resulting floor plan that is generated automatically from the point cloud representation using the initial version of the Floor Plan Generation software component. Furthermore, we discuss the use of simulated 5G signals for localization estimation, and provide examples of generating a routing graph from the approximated 2D floor plan as well as from the as-is IFC LOD 300 model of the entire floor area. We use these routing graphs for the computation of an optimal path for aiding in indoor navigation tasks. Finally, we present the initial visualization results running on a Web3D-enabled browser on a commodity client computer.

A. Point Cloud Processing

For the point cloud processing results, the point cloud of the fourth floor area of the university building is generated using simulated laser scanning. We make use of the as-is LOD 300 IFC model, from which we extract a triangulated mesh, and sample points using uniformly distributed point sampling for each of the mesh triangles [63]. Once generated, further processing is performed via the Point Cloud Processing software component, using the Open3D Python framework [64] for key processing tasks (Fig. 7). These key tasks include: sub-sampling, outlier point removal and geometric segmentation. The result of these processes are point clusters representing key structural elements which can be used as floor plan layers. Registration was not performed for this case study, though the implementation is capable of accomplishing this using automated registration methods, e.g., Iterative-Closest Point (ICP) matching algorithm [65].

After sub-sampling, using a voxelized sampling to ensure uniform removal of points, the original point cloud is reduced to a fraction of its original points (approx. 75% of points are removed). The overall visual fidelity of the point cloud is preserved, while increasing the coarsity and removing redundant overlapping and closely spaced points. For the outlier point

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removal, a statistical outlier removal method was used [66], where the points forming clusters that are considered too far away from the main point cluster groups were removed. This enabled the removal of outlier points especially noticeable at the edges of the sub-sampled point cloud. Finally, the point clusters representing the planes of key structural components (namely walls, floors and ceilings) are detected and segmented using the iterative RANSAC method, which attempts to fit matching points to a set number of hyperplanes [67]. The horizontal point clusters forming the floor representation are then used for the 2D floor plan approximation by the Floor Plan Generation component.

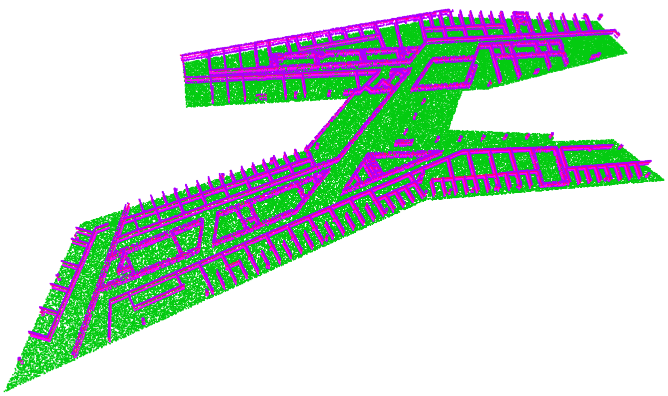

Fig. 7. Initially segmented point cloud, with the main floor plan boundary and secondary wall structure boundaries displayed.

B. Floor Plan Generation

A 2D floor plan can be generated either from the existing as-is BIM (i.e., IFC model), or from the as-is point cloud representation. Generating the 2D floor plan from the IFC requires selecting each building storey element and projecting it onto a 2D plane, where each of the IFC components are rendered as vectorized paths and associated element semantics, and exported together as a SVG file [68] . This SVG file is then further parsed and converted to a GeoJSON [69] file (Fig. 8), which can then be used as 2D floor plan data for required indoor navigation tasks.

Fig. 8. An example of a semantically-rich GeoJSON file, containing vectorized paths along with IFC element shapes and semantics (e.g., a wall element).

A 2D floor plan can also be approximated from a horizontally sliced layer of the post-processed point cloud. The initial 2D concave or convex hulls of this point cloud layer (including both primary and secondary shape boundaries, i.e., shapes within shapes), are approximated based on the approach described in Stojanovic et al. (2019) [24]. This allows for the capture of boundaries of the floor plan, using adjustable parameter values (Fig. 9). Once the initial boundaries are approximated, they are simplified as their resulting boundary shape is usually noisy. The resulting 2D floor plan approximation is then exported as a GeoJSON file.

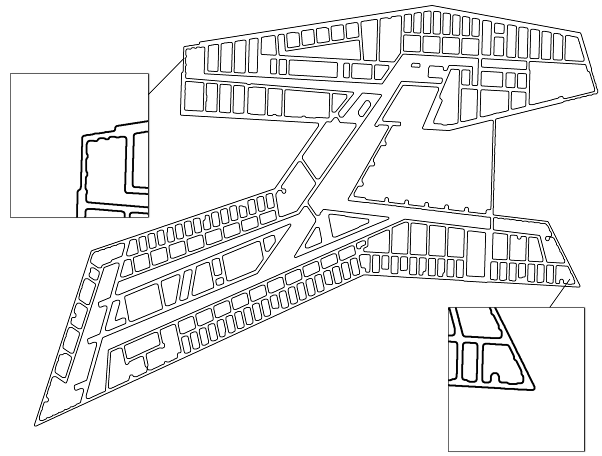

Fig. 9. A generated floor plan based on a point cloud, with boundary evaluation errors that need to be corrected in further post-processing steps.

C. 5G Simulation and Localization

Using the Simulated 5G Capture components, the antenna placement and three 5G positioning signals are simulated (Fig. 10). This is calculated based on some reference points and given noise. In this way, one may simulate 5G-based coordinates with different precision. This is needed for fusion algorithms when such a simulated infrastructure-based positioning has a high range of noise. One can enter the number of desired antennas and positions. Then, they can be entered to the simulated environment and by calling a calculation function, the predefined noises, frequencies and some measurement results can be computed.

D. Optimal Path Approximation

The optimal path generation is performed using the generated routing graphs either from the 2D floor plan or the 3D floor plan derived from the as-is IFC representation. For routing graph generation of 2D floor plans, we make use of a generalized Voronoi-based medial axis transform [50], in order to generate 2D line graphs representing navigable areas (Fig. 11(a)), while for routing graph generation from the 3D floor plan we use the triangulated mesh of the floor element boundary representation in order to generate a "navigation mesh" [10] (Fig. 11(b)).

For computation of the shortest paths using routing graphs, we make use of the A* shortest path algorithm [70]. The A*

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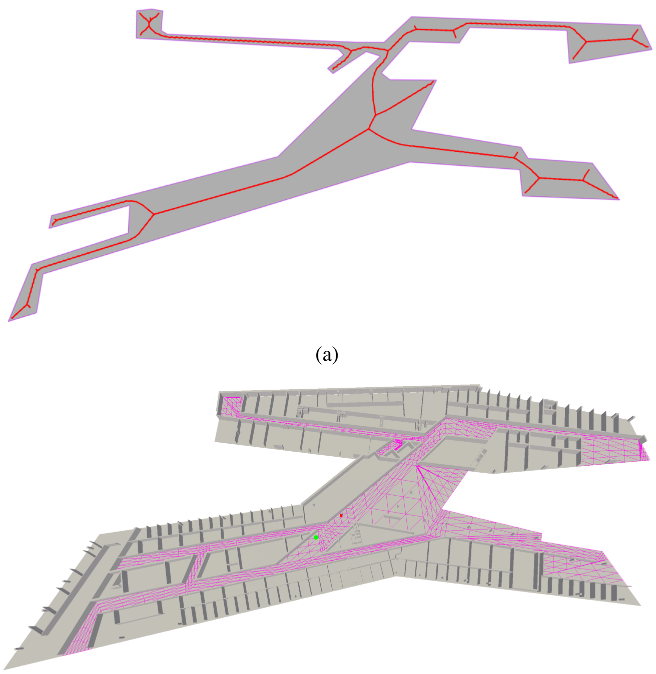
Fig. 10. An example of localization of three points (red circles) in the simulated environment, with six different 5G antenna placements. This simulation component is tested via a simple user interface that allows the placement of 5G antennas anywhere on the vectorized GeoJSON version of the 2D floor plan (generated from the as-is BIM representation).



(a)

(b)

Fig. 11. (a) An example routing graph of a navigable floor plan area variant, based on the approximated primary boundary of the 2D floor plan. (b) An example routing graph/navigation mesh (purple) of the main navigable areas of the floor plan, based on the triangulated 3D model of the as-is BIM representation.

algorithm uses the vertex and edge connections that form the routing graph, in order to evaluate and construct the shortest navigation path. This approach was tested using the 3D model of an as-is BIM (Fig. 6). For testing the 3D floor plan and routing graph, the generated shortest path computation allows the user to select and set starting and ending points, between which the shortest path will be computed (taking into account any obstacles, e.g., walls that may be in between the starting and ending points (Fig. 12)).

VI. Discussion

We have presented a conceptual SOA and prototypical implementation of key SOS components for integrating 5G,

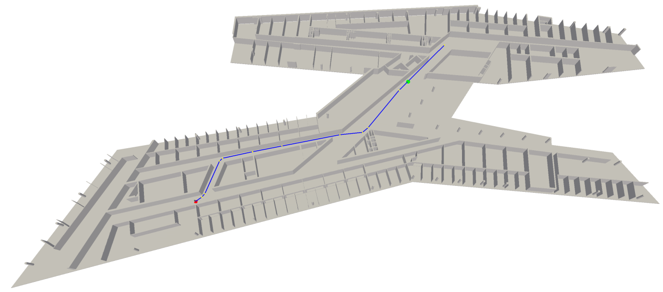


Fig. 12. An example of shortest path (blue) computation result between the starting and current point (green) and ending point (red) – based on the result of the A* algorithm and making use of the underlying routing graph (i.e., navigation mesh).

BIM and point cloud data for DT representations of indoor built environments. For our case study, we have focused on the topic of indoor navigation, using an approach of combining point clouds, 2D floor plans, BIM and simulated 5G signal data. We can create 2D floor plan approximations from input point clouds, and derive and generate routing graphs from both 2D floor plans and 3D models (obtained from BIM data). Using the 5G-based simulated coordinates, we are able to simulate the expected localization approximation corresponding to the indoor areas within the university building - where the expected 5G infrastructure will be operational in the near future. In this way, one can approximate the user's indoor position. We further combine this with optimal path generation between the user's current location and target destination. The generated routing graphs are used with search algorithms to calculate the shortest path and visualize it within a 2D/3D floor plan context. The fusion of the outputs of all of these results from the SOS components is presented interactively via a Web3D interface, where the user can inspect the as-is point cloud, 2D floor plan, 3D BIM model, current approximated location and optimal path results. Our presented approach is based on the DT paradigm, which has evolved from previous research mainly focusing on BIM-based and IoT integration approaches [71] - though such approaches do not take into account, e.g., dynamically updated systems, frequently changing built environment states and indoor space configurations, and are not designed to predict future states. Apart from a Web3D-based approach for interactive visualization of the results obtained using service-oriented computation, another approach can be the use of existing game engines for computation and presentation for FM scenarios [72]. The use of the SOS paradigm is also not the only way to implement DT solutions, and approaches based on, e.g., Supervisory Control and Data Acquisition (SCADA) [73] and Enterprise Resource Planning (ERP) [74] have also been investigated as potential architecture solutions in previous research.

VII. Conclusion

We have proposed our approach based on a concept of a DT, which enables the fusion of historical, current and predicted (or simulated) data sources for processing, analysis and representation – within a service-oriented paradigm. We have implemented and tested all of the key software components responsible for processing, analysis and visualization of key data sources needed to generate valuable information about localization and indoor navigation within a university campus building. We have identified the use of point clouds as a key source for as-is representation of indoor environments, alongside existing as-is/as-built BIM data (e.g., IFC models, point clouds, etc.). We have presented and discussed methods for generation of approximated 2D floor plans from point clouds, and the generation of routing graphs from such floor plans as well as 3D mesh representations derived from existing IFC models. Finally, we have implemented and described state-of-the art approaches for routing graph and optimal path computation. We have designed a simulation for 5G-based coordinate estimation to overcome with the localization task. The presented approach lays a solid foundation for future work focusing on developing a versatile indoor navigation software solution based on the DT and service-oriented computing paradigms.

The use of simulation processes for generation of point cloud and 5G sensor and signal data has enabled the rapid development and testing of the key software components – without needing to source such data from complex or non-existent sources. For future work, we plan to evaluate our approach using real-world point clouds captured using laser scanning as well as make use of the planned 5G infrastructure for capturing real signal and sensor data. The positioning approaches can achieve the fusion of sensor data, infrastructure input and consider the map matching features. While we make use of a DBMS for storage for data, we did not explicitly evaluate its performance for data retrieval and queries, and this is also planned for future work. We also plan to further optimize and improve the 2D floor plan generation methods, in order to have better approximations of secondary boundaries. Finally, our future work will focus the further development and integration of DT and 5G paradigms focusing FM related scenarios (e.g., real-time data can be fed into a DT with the help of 5G and serve to actively control the flow of people and the operational capacity of the building).

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