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Visualizing intrusions in dynamic building environments for worker safety

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ABSTRACT

A review of the existing literature suggests that intrusions on sites are often overlooked as current construction safety assessment methods are primarily focused on visible consequences such as injuries and deaths. Moreover, traditional Behavior-Based Safety (BBS) methods for improving worker attitude towards adopting safety practices on work sites are not adequate as these methods do not provide quick feedback for changing unsafe worker behaviors in real-time to avoid fatalities. Consequently, geo-localization systems are used for acquiring spatio-temporal trajectories to identify unsafe worker behaviors on construction sites. However, spatio-temporal trajectories lack contextual building or site information. For incorporating the geographical and application-specific context in trajectories, semantic enrichment processes are executed. The semantic enrichment process should include changing contextual information related to the evolving building objects over time. The changing contextual information of building objects is required to be tracked by a system to study the worker behaviors in a dynamic building environment context. After reviewing the existing literature, it is concluded that none of the present systems offer a mechanism to identify unsafe worker behaviors such as intrusions in dynamic environments where the contextual information of building spaces evolves over time in terms of location, size, properties and relationships with the environment. To fill this research gap, a system is proposed; First, to acquire the worker movements using Bluetooth Low Energy (BLE) beacons. Second, to perform the pre-processing as well as semantically enriching the spatio-temporal worker trajectories using relevant updated contextual information of a building. Lastly, to visualize the building locations where intrusions have occurred using Building Information Modeling (BIM) approach. The developed system presents an integration of systems from the data acquisition stage to visualizing the unsafe work behaviors that could serve as a foundation for future research in studying advanced movement-related worker behaviors in dynamic environments by overcoming the spatio-temporal data management challenges.

1. Introduction

Intrusions are unauthorized staying-in or stepping into the hazardous areas without realizing the potential dangers associated with the locations and are very common type of near-miss incidents occur frequently on construction sites (Heng et al., 2016). The Health and Safety Executive (HSE) working in the UK describes near-misses as unsafe acts that are potentially hazardous events and can cause ill health and fatalities (HSE, 2018). Herbert Heinrich first theorized that a serious injury often occurs after many less severe first-aid injuries and near misses, and that these incidents happen in a fixed ratio of 300 near-miss incidents to 29 first-aid injuries to 1 serious injury (Heinrich, 1931) as shown in Fig. 1. The near-misses (intrusions in our case) are required to be analyzed for avoiding non-fatal injuries that will eventually decrease the rate of fatal and non-fatal accidents on sites (Heinrich, 1931; Bellamy, 2015). The intrusions not only cause unauthorized workers to get affected and suffer from an accident but can also interrupt or even harm other workers in the hazardous site zones (Huang and Hinze, 2006). Intrusions on sites are often overlooked as current construction safety assessment methods are mainly focused on visible consequences such as injuries and deaths (Heng et al., 2016). The major reason for getting neglected is because of the complexity in recognizing near-misses involving intrusions and providing feedback in real-time during construction operations (O'Neill et al., 2013). To solve this problem, Behavior-Based Safety (BBS) trainings (Guo et al., 2018) are usually conducted to improve the worker attitude towards organizing a better safety culture on sites. Regardless of many successful implementations of BBS trainings in many construction projects, they

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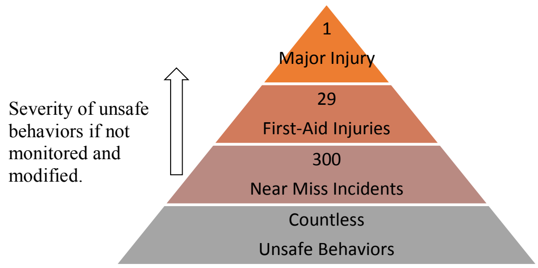

Fig. 1. Modified Heinrich's triangle (Heinrich, 1931).

have limitations as well such as; (1) unable to overcome the worker limits to identify all surrounding hazardous zones, and (2) mostly relying on the physical inspections by well-trained safety supervisors and failing to provide quick feedback to change unsafe worker behaviors in real-time (Fang et al., 2018a, 2018b; Heng et al., 2016).

To overcome the limitations of BBS trainings and to monitor worker behaviors in real-time for minimizing the near-misses, sensing and warning-based technologies (Jia et al., 2019; Awolusi et al., 2018; Lin et al., 2019; Chen and Lu, 2019; Gheisari and Esmaeili, 2019) are utilized in the existing literature for the development of intrusion warning and proximity detection systems (Dong et al., 2018; Heng et al., 2016; Fang et al., 2018a, 2018b; Naticchia et al., 2013; Pradhananga and Teizer, 2013). The developed systems based on sensing and warning-based technologies such as Radio Frequency Identification (RFID), location estimation using 802.11, Global Positioning Systems (GPS) and Indoor Positioning Systems (IPS) are used for; (1) acquiring spatio-temporal data of workers and the site environment to understand mobility dynamics of workers and operational machinery in relation to the site environment, (2) executing safety risk assessment methods on the acquired sensor data, (3) generating accurate and timely warnings to the construction workforce (construction workers and machinery operators) for triggering Health and Safety (H&S) interventions to improve personal behavior during hazard proximity conditions, and (4) disseminating the information of near-misses to site supervisors and H&S managers for quick actions for maintaining site safety (Antwi-Afari et al., 2019). The objective of these systems is not only to construct proactive surveillance methods for site supervisory staff and H&S professionals for protecting the H&S of frontline workers while working in hazardous situations on sites but also indirectly lowering the costs of construction projects by reducing the occurrences of accidents on sites (Teizer et al., 2010; Antwi-Afari et al., 2019). The spatio-temporal datasets collected for the development of the systems as mentioned above consist of ordered sequences of discrete-time triples in the form of ⟨latitude, longitude, timestamp⟩ called as trajectories (Zheng, 2015). These trajectories are treated as approximations of the real mobility data of moving objects (Zheng, 2015; Yan and Spaccapietra, 2009). However, spatio-temporal trajectories lack contextual building or site information and require semantic enrichment processes. A conventional semantic enrichment system enriches trajectory points with the information of a building or site environment captured from the openly available or private data sources (geo-databases, site information etc.) to incorporate application-specific geographical (site locations such as work-zone, material-zone, etc.) and behavioral context in trajectories (Parent et al., 2013; Albanna et al., 2015).

Enriching trajectories with the semantics of space (e.g. the locations, where trajectories were generated), and the semantics of time (e.g. time interval having a start and stop timestamps) give more meaning in discovering movement-related behaviors of the workers on sites (Parent et al., 2013). For performing the semantic enrichment process, we need a trajectory data model that should be capable to hold up-to-date semantic information of a building or site objects (e.g. locations) which evolve over time in terms of their position, size, properties, and relationships with the environment as the construction work progresses (Arslan et al., 2019b). For example, new walls and infrastructure supports are often added over time on sites, while others are detached. Also, changes in the dimensions or the purpose of the locations resulting in a change in the associated semantic information (e.g. alphanumeric properties) of the building locations (Arslan et al., 2019c). For capturing this building evolution, this work reports upon using a trajectory data model named Semantic Trajectories in Dynamic Environments (STriDE) to semantically enrich spatio-temporal data of workers in dynamic environments using up-to-date contextual information to detect unsafe behaviors which are intrusions in our case (Arslan et al., 2019a; Cruz, 2017). Finally, for visualizing the intrusion information, BIM platform is used. The National BIM Standard (NBIMS) describes BIM as 'a digital representation of physical and functional characteristics of a facility that provides a shared digital representation founded on open standards for interoperability' (NBIMS-US, 2015). BIM is chosen because the existing literature identifies it as the most preferred and widely used approach as compared to traditional 3D CAD approaches in the industry (Becerik-Gerber et al., 2011). Moreover, BIM provides a platform for efficient information management during the building lifecycle for safety analysis (Shen and Marks, 2015). For our study, Autodesk Revit (i.e. a BIM software) is used because it provides an open-source Application Programming Interface (API) support and extensive use in the industry (Das et al., 2015). For taking benefits from the functionalities accessible using a Revit API, a visual scripting tool Dynamo is used which functions as a Revit plug-in. The main advantage of using a Dynamo is that it has the power for constructing programmatic relationships using a graphical user interface without extensive coding (Autodesk, 2017). Dynamo also offers a coding option using Python language to developers for configuring 'code blocks' which are special nodes in Dynamo for executing advanced user-customized operations if required (Autodesk, 2017).

The rest of the paper is organized as follows: Section 2 presents the background literature. Section 3 is based on the proposed prototype scenario presentation and system implementation in which trajectory data of building users is collected, processed, semantically enriched using a data model, and intrusions are visualized using a BIM model. Section 4 presents the discussion on; (1) the level of spatial, temporal and occupant resolution targeted for the semantic enrichment of spatio-temporal trajectories for the developed system, (2) the measurement data analysis for better accuracy in identifying the building locations for detecting intrusions, (3) the accuracy of location identifications using BLE beacons, and lastly the strategy used for analyzing the positioning errors in semantic trajectories. Section 5 presents a conclusion and the limitations of the presented study.

2. Background

Unsafe behaviors of workers are the major cause of fatalities on construction job sites (Zhang et al., 2019; Teizer et al., 2013). Infringing the certain areas on construction sites where the workers are not authorized to access called intrusions which are one of the examples of unsafe behaviors. Intrusions often occur when workers take shortcuts to move around the site without identifying the potential dangers associated with such locations where they are not allowed (Wu et al., 2010; Heng et al., 2016). Intrusions result in different turbulences in the construction site operations and may lead to serious safety concerns that can potentially affect an intruder and the other workforce on a construction job site (Wu et al., 2010).

2.1. Existing systems for detecting intrusions

In this section, a comprehensive review (see Table 1) is done on state-of-the-art systems used for preventing intrusions on sites for safety management. The studies presented by Heng et al. (2016), Shuang et al. (2019) and Naticchia et al. (2013) are the most relevant examples of detecting intrusions on construction sites using wireless communication

Table 1
Existing Safety Monitoring Systems for Preventing Intrusions.

Use cases	Building environment	Dataset	Findings	Key components and technologies
Intrusion warning and assessment system (Heng et al., 2016)	Outdoor	Location trajectories of 3 workers during 6 h in day	Developed a multi-user platform for obtaining the worker positions in relation to virtual hazardous zones	Real-Time Locating System (RTLS) consisting tags
Identifying and recording intrusion behaviors on construction sites (Shuang et al., 2019)	Outdoor	147 construction workers' data over a 4-month period	Analyzed the effect of age and gender of construction workers on the frequency of intrusions	BIM and RTLS
Controlling interferences on sites using a real-time monitoring system (Naticchia et al., 2013)	Outdoor and indoor	600 positioning records sampled at 5 min.	Stored and maintained workers site interactions and detected interferences	IEEE 802.15.4 standard medium access
Preventing near miss interactions between construction resources (Golovina et al., 2016)	Outdoor	70 min long trajectories of a worker and a skid steer loader.	Recorded, identified, and analyzed hazardous near miss situations between workers and heavy construction equipment	GPS
Detecting non-certified work on sites (Fang et al., 2018a, 2018b)	Outdoor	Public datasets (WIDER FACE dataset and CelebFaces + dataset)	Non-certified workers are detected using video imaging technology and notifications are generated to cease their activities	Vision-based deep learning algorithms
Preventing workers from accessing hazardous areas using a proactive system (Carbonari et al., 2011)	Indoor	–	Warnings are generated to inspectors before the occurrences of the interferences	Ultra-Wide Band (UWB) technology
Constructing a model after analyzing historical accidents cases to prevent accidents (Wu et al., 2013)	Outdoor and indoor	499 accidents cases from 1990 to 2008.	An integrated information management model is built to track struck-by-falling-object accidents	ZigBee and RFID technology
BIM and cloud-based indoor localization system (Fang et al., 2016a, 2016b)	Indoor	–	Performed real-time data processing and generated visualization for remote monitoring for detecting intrusions	Passive RFID system
Implementing a proactive accident prevention solution (Yang et al., 2012)	Outdoor	4,640 accident cases from U.S. OSHA database.	Analyzed the automatic identification requirements consisting of access control, training and inspection information and operation authority	ZigBee and RFID technology
Presenting a safety early warning system in underground construction (Ding et al., 2013)	Underground	–	Designed and validated an IoT based safety system on the construction site to provide information about dangerous situations in advance	A fiber Bragg grating (FBG) sensor system and a RFID
Proximity hazard indicator for near miss interactions (Teizer and Cheng, 2015)	Outdoor	–	Automatically identified the areas of static and dynamic hazards on a construction site	UWB localization system

technology. The system proposed by Naticchia et al. (2013) is based on the ZigBee protocol offering a self-healing and easy to deploy solution for detecting intrusions on sites using the notification system by triggering alarms when workers get closer to the boundaries of pre-determined work areas. Intrusions involving the workers who carry out any construction activity without an appropriate training pose a great risk to construction safety. A framework proposed based on deep learning methods by Fang et al. (2018a, 2018b) uses the images of workers obtained from the videos to capture their identification and checks whether an on-going work is being carried by the certified workers or not. A similar study is conducted by Carbonari et al. (2011) in which a system is developed to implement virtual fencing logic using ultra-wideband technology for preventing workers to access predefined hazardous zones. The system also offers real-time notification service to safety managers by proactively generating warning messages if the risk level to access the hazardous zone increases. While, in their case-study, the hazardous zones are pre-defined. However, construction sites are very dynamic in nature where nature of locations changes over time. Further research should be done to test the use-cases which involve dynamically changing hazardous zones for implementing virtual fencing logic on construction sites.

Existing literature also deals with safety monitoring solutions which are developed based on the requirements acquired from the historical data of accidents for further preventing the near-miss incidents. An example of such model is described by Wu et al. (2013) in which information requirements for preventing struck-by-falling-object accidents are collected, and based on these requirements, a system is built using ZigBee-RFID sensor network for tracking workers and materials on sites along with their identity information. Moreover, Fang et al. (2016a, 2016b) designed, and developed a system primarily for indoor localization to monitor sites for safety management. Taking the benefits of BIM, their system can able to track workers and materials by displaying their locations on a BIM model. The proposed system fits its application best in the early warning systems where the proximity of workers and construction materials to hazardous locations is monitored in real-time for proactive accident prevention. Another similar study is presented by Yang et al. (2012) based on the application of ZigBee-RFID sensor network to track identity information of workers. The system is developed based on the requirements collected after analyzing historic case-studies relating to near-miss accidents. The analysis concluded that access control, training and inspection information, and operation authority of on-site workers, machinery and materials are three major aspects for developing an automatic identification system for site safety. Besides outdoor and indoor safety monitoring systems for preventing intrusions on job sites, there also exists systems in the literature for preventing accidents in underground construction scenarios. Ding et al. (2013) conducted a study in an underground metro tunnel construction project based on Fiber Bragg grating (FBG) sensor system and an RFID. They designed and validated an IoT-based safety system in an underground construction job site to provide information about dangerous situations in advance.

In summary, after reviewing existing systems for preventing intrusions on construction sites, a closely-coupled data communication platform between the workers and site locations is required for tracking the dynamic interactions of the workers with the site environment for generating timely alerts to provide quick feedback to the workers for changing their unsafe behaviors in real-time. The resulted alerts will help in decreasing the intrusions which ultimately lower the rate of fatalities on construction job sites.

2.2. Semantic enrichment of spatio-temporal data

For tracking the dynamic movements of the workers for recognizing their unsafe behaviors, related literature on location data acquisition technologies is also studied (Li et al., 2017; Luo et al., 2016a,b; Yu et al., 2017; Pradhananga and Teizer, 2013; Cheng and Teizer, 2013).

This review suggested IPS-based systems are recommended over GPS-based systems and have been used widely in developing the applications for analyzing worker behaviors (Woo et al., 2011; Khoury and Kamat, 2009). However, the raw location datasets called spatio-temporal trajectories acquired from IPS-based systems are only suitable for certain systems which aim at locating moving objects and performing statistics based on the spatio-temporal features (Arslan et al., 2018; Parent et al., 2013). For instance, where was John at 10 am? Or identifying the locations where the density of the trajectories is higher, etc. Majority of the systems need additional information from the application context to complement the spatio-temporal trajectories (Parent et al., 2013). For example, understanding the trajectories of workers on a construction site need information about the site or building features (e.g. work-zone, material-zone, dumping-zone, etc.) (Pradhananga and Teizer, 2013). Thanks to OpenStreenMap (OSM) and BIM data files which allow us to replace geographical coordinates in raw trajectories with the location names or with the names of Places of Interest (POIs) to provide the geographical building or site context in trajectories (Arslan et al., 2019b). This additional contextual information extracted from the external data sources (OSM, BIM, etc.) is called annotation and a process of adding different annotations to trajectories is called a semantic enrichment process (Arslan et al., 2019c; Parent et al., 2013; Yan, 2011).

For enriching trajectories with the semantic information, there exist four basic types of modeling approaches which are; (1) data type-based, (2) design pattern-based, (3) ontology-based, and (4) hybrid-based modeling (Albanna et al., 2015; Arslan et al., 2019c). The comparison of these approaches in terms of their applications is stated in Table 2. Data type-based modeling represents trajectories as an Abstract Data Type (ADT) and combines spatial, temporal and thematic dimensions to represent the trajectory data (Frihida et al., 2009). Data type-based modeling approach is not adequate to generate semantic trajectories for an extensive range of applications because it restricts the usage of a general data type for representing semantic trajectories for all the applications. To overcome this limitation, pattern-based modeling supports spatial, temporal objects and their relationships using a method to describe trajectories in the form of 'stop' and 'move' segments having 'begin' and 'end' timestamps (Parent et al., 2006). However, this segmentation method requires manual inputting the contextual information in the model (Albanna et al., 2015). Ontology-based models also exist to overcome the limitations of the former two modeling approaches discussed above. Ontology-based models generate semantic trajectories with richer semantic information using external data sources. In these models, initially, segmentation approaches are used to output the structured trajectory episodes (Albanna et al., 2015). Later, these trajectory episodes are mapped on ontologies for annotating them with relevant POIs‘ information. Ontology-based models offer many benefits such as tagging of semantic locations and their environmental properties, clustering of similar trajectories based on the common behavior or activity, reducing trajectories for visualizations, segmenting trajectory episodes into stop and move episodes and determining the transportation mode used in the move episodes of the trajectories. Examples of these models are provided by Fileto et al. (2013, 2015) and Nogueira (2017) studies.

2.3. BIM support for visualizing safety information

After constructing the semantic trajectories and storing them in a trajectory data model, a BIM software is used for visualizations. The BIM is a dynamic workbench in the Architecture, Engineering and Construction (AEC) industry which integrates different types of construction and facility management information into a digital model that can be used for all phases of a building lifecycle (Tang et al., 2019). The application of BIM is presently going through tremendous growth in enhancing safety in building operations, planning and management (Azhar et al., 2012). Existing studies show that potential safety hazards can be identified automatically by examining the BIM-based digital models along with the construction schedules after executing safety risks detection rules in BIM software (Sulankivi et al., 2013) The BIM model is continuously updated over time as construction progresses to bridge a gap between construction operations and digital data (Azhar et al., 2012). However, it lacks the functionality of assessing the current state of the building environment in real-time for H&S management (Riaz et al., 2017; Stojanovic et al., 2018). Here, a state of a building location refers to its environmental data (e.g. temperature, humidity, etc.), the status of workers (e.g. tracking, occupancy monitoring and identifying their actions), analyzing the utilization rate of machinery, and performing localization and preventive maintenance of building objects for different BIM-based application scenarios (Tang et al., 2019). The BIM data needs to be constantly updated with the current state of the building environment to accommodate the real-time monitoring of building locations for safety management (Riaz et al., 2017). To incorporate the building environment data, wireless sensor technology has gained great importance in real-time monitoring of the buildings. The wireless sensors are often low-cost nodes and typically connected to the internet for data transmission (Arslan et al., 2014). Numerous attempts to enrich the BIM data by incorporating the real-time data collected from different wireless sensor technologies have already been made to specifically improve: environmental monitoring (Natephra et al., 2017; Zhong et al., 2018), building energy performance (Habibi, 2017), controlling building objects (Rashid et al., 2019), facility (Wong et al., 2018) and H&S management (Chou et al., 2019; Park et al., 2017; Cheng et al., 2017; Park et al., 2016). The studies mentioned above motivate to develop a BIM and sensor-based integrated solution for improving the safety of the workers on sites. As a generalization, a BIM and wireless sensor technology-based solution will offer complementary views of the building which together overcomes the limitations of each (Tang et al., 2019). BIM models provide building representations which are viewed as a collection of virtual assets by including the geometry, spatial locations of the building

Table 2
Existing Trajectory Models And Their Application (Arslan et al., 2019b).

Model	Type of model	Building environment	Application*									
			A	B	C	D	E	F	G	H	I	J
MADS (Spaccapietra et al., 2008)	Design pattern and dedicated data types	Outdoor				X						
SeMiTri (Yan, 2011)	Object-relational	Outdoor	X	X		X	X			X		X
The Baquara (Fileto et al., 2013)	Ontological	Outdoor	X			X	X			X	X	X
CONSTAnT (Bogorny et al., 2014)	Relational	Outdoor	X			X	X			X	X	X
The Baquara^2 (Fileto et al., 2015)	Ontological	Outdoor	X	X	X	X	X			X	X	X
SemMobi (Wu et al., 2015)	Document-oriented	Outdoor	X	X		X		X	X			
FrameSTEP (Nogueira, 2017)	Ontological	Outdoor	X	X		X	X				X	X
SMOPAT (Semantic MObility PATterns) (Wan et al., 2018)		Outdoor	X	X		X						

* **A** = Identification of locations; **B** = Clustering of trajectories; **C**: Trajectory reduction; **D**: Trajectory segmentation; **E**: Transportation mode detection; **F**: Prediction; **G**: Recommendation; **H**: Activity recognition; **I**: Mapping with the environmental information; **J**: Behavior categorization.

Table 3
BIM-Sensor-Based Solutions for Safety Management.

Reference	Use case	Sensors involved	Purpose of sensor
Chou et al. (2019)	Optimal path planning for dynamic building fire rescue operations	BLE sensors, global positioning information	Collecting fire scene information (ignition points, locations of trapped occupants, and locations of firefighters)
Zhou et al. (2019)	Cyber physical system-based safety monitoring for blind hoisting	Ultrasonic positioning, laser ranging, and 3D gyroscope device	360° monitoring of the common reasons of hoisting failures
Chen et al. (2018)	Visualization and warning system for fire rescue	Grove flame sensors	Information retrieval from the fire scene
Park et al. (2017)	Hybrid knowledge-based integrated system	BLE and motion sensors	Increased the overall reliability of the worker tracking
Cheng et al. (2017)	Smart monitoring for building fire prevention	BLE sensors	Fire detection and localization
Park et al. (2016)	Automated construction-safety monitoring using cloud-enabled BIM	BLE sensors	Location detection
Kim et al. (2016)	An automated hazardous area identification model	Real-time location system (RTLS)	Identifying a hazard and decreasing the time workers are exposed to a hazard
Shen and Marks (2015)	Near-miss information visualization	Manual data inputted by users and data from external databases	Viewing near-misses in BIM for identifying hazardous areas and frequency of near-misses

components and their set of properties at the component level (Tang et al., 2019). Whereas, wireless sensor technology complements this information by offering real-time status from the actual building environment. With the help of APIs, BIM and wireless sensor data can be integrated to provide real-time control over the workers, machinery, building objects and, work environment. This integrated information can be used by the H&S managers for timely identification of the safety risks on sites. The most relevant BIM and sensor-based systems related to our work are mentioned in Table 3. For more details on the benefits of BIM and sensor-based solutions and existing methods of integrating BIM and sensor data, see an article by Tang et al. (2019).

The BIM and sensor-based integrated solutions as discussed above provide countless benefits to the AEC industry by providing a centralized digital building model enriched with the real-time sensor data (Riaz et al., 2017; Volk et al., 2014). Once the building model is modified by incorporating the spatial and contextual (i.e. alphanumeric properties of locations) changes by the AEC managers during the construction stage, the previous as well as the updated information of building is managed using Industry Foundation Classes (IFC)-based system which enables the exchange of BIM data for different building monitoring applications (Volk et al., 2014). This case is not only limited for the construction phase of buildings but also applies to rest of the building phases where the building undergoes spatial evolutions less often but more frequent changes in the contextual information linked to building locations (Akcamete et al., 2010). The historical BIM information involving the spatial and contextual evolutions during a building lifecycle needs to be integrated with the real-time trajectory data of building users so that different behaviors of building entities (users and equipment) can be studied in detail with respect to the type of changes occurred in the building environment (Arslan et al., 2019c). The historicization of building information along with user trajectory data will help AEC managers for conducting 'cause and effect' analysis. For example, extracting the type of spatial or contextual changes occurred in the building infrastructure which resulted in near-miss incidents in a building.

3. Proposed system

After reviewing existing intrusion detection systems, it is concluded that spatio-temporal data is extensively analyzed to avoid near-miss incidents on construction sites. However, previously designed systems do not offer a mechanism to recognize near-misses such as intrusions in dynamic environments where the building locations change over time in terms of their position, size, properties, and relationships with the environment. New infrastructural support such as walls, etc. are added often on construction sites, while others are detached (Arslan et al., 2019c). This opens more challenges to keep track of the changes in the contextual information associated with the locations which involve over time for identifying intrusions from the perspective of the building or site environment. To fill this research gap, the most relevant modeling approaches for constructing semantic trajectories using spatio-temporal are reviewed. This literature review suggested that ontology-based modeling is the most preferred approach for enriching user trajectories with the relevant semantic information as ontologies provide the convenience of sharing, exchanging and reusing the domain-specific knowledge (Fensel, 2002). However, the existing trajectory models are intended specifically for outdoor environments and these models provide restricted support for modeling semantic trajectories within the building settings (Arslan et al., 2019b). In addition, these models do not adequately cater to the trajectory modeling requirements for indoor dynamic environments where the building infrastructure is evolving over time. Hence, these modeling approaches are not suitable for identifying intrusions on a construction site which is the best example of an indoor as well as an outdoor dynamic environment.

For developing a prototype system entitled '*VIDEWS*' (Visualizing Intrusions in Dynamic Environments for Worker Safety), a two-phase process is adopted. First, a scenario is designed that sought to provide a 'blueprint map' to integrate all the elements required to build an intrusion detection system for dynamic building environments, more specifically the construction sites. Second, the created scenario is then transformed into the prototype system development environment.

3.1. VIDEWS scenario presentation

This section presents the description of the scenario for *VIDEWS* from the user perspective. The two roles, which are 'building supervisor' and 'Health and Safety (H&S) manager' are considered in developing the scenario (see Fig. 2). The working of the scenario initiates as the Graphical User Interface (GUI) for extracting the information of detected intrusions is invoked from the BIM software. The system interactions which were involved in creating this GUI functional are stated below;

1. For collecting the worker movements in a dynamic building environment, the BLE beacons are mounted on different locations in buildings. The handheld devices of workers capture three strongest detectable signals of neighboring BLE beacons, estimates the locations in the form of spatio-temporal points using the beacon deployment map information and forward them to the nearest Access Points (APs) for storing them in a centralized database.
2. The spatio-temporal points of the workers are enriched with their corresponding building locations using the geographical information extracted from the OSM files of buildings and later stored in an ontology-based STriDE data model (i.e. a triplestore) with the

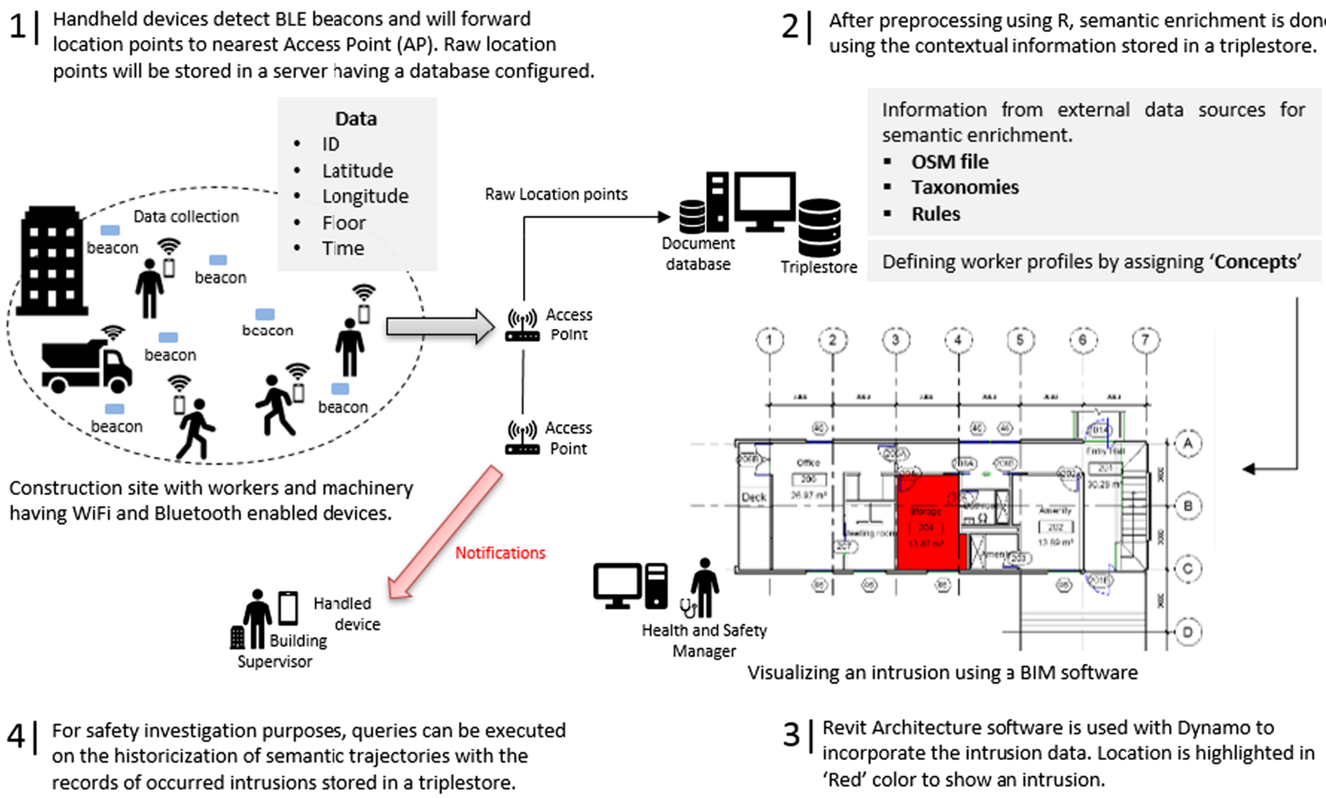

Fig. 2. Prototype system scenario for identifying intrusions on a construction site.

information of worker profiles for historicization.

3. Using the information stored in a triplestore, the intrusions are detected. The output of a triplestore is linked with the BIM software for visualizing the building locations where the intrusions have occurred.
4. All the information of intrusions with the building evolution will be stored in a triplestore for future investigation purpose and will help in conducting cause and effect analysis on the occurrences of near-misses on sites.

3.2. VIDEWS prototype

This section presents the functionality of the developed *VIDEWS* system which is constructed for detecting intrusions in dynamic environments for worker safety. The scenario presented above is created ideally for the construction sites where the locations evolve over time in terms of location, size, properties and relationships with the environment. However, the functionality of the scenario is validated in two already constructed educational buildings where the locations only evolve in terms of contextual information (i.e. alphanumeric properties). BLE beacons are chosen for spatio-temporal data collection of building users because of their portability, easy to deploy and low-cost solution (Paek et al., 2016). The geographical information extracted from the OSM files of buildings is used for constructing the beacons‘ deployment plan to cover all the possible building locations for data collection. Real-time user movements in two buildings are collected in a batch mode (Zheng, 2015) for a period of 2-weeks. Later, the user movements are enriched with their corresponding building locations and user profiling is achieved. Lastly, the detected intrusions are visualized using BIM software. The BIM files of buildings where the movement data is collected do not exist. To demonstrate the proof-of-concept integration of systems and the working of Revit API, a sample BIM model is used for linking it with the information of intrusions extracted using a triplestore. For integrating the information of intrusions with corresponding building locations in a BIM model, unique room identifications are used and made identical in BIM as well as in the STriDE model. The details of the subsystems of a developed prototype are mentioned below.

(1) Location data acquisition and preprocessing

For collecting the spatio-temporal data to detect intrusions, around 200 BLE beacons were installed in two buildings (see Fig. 3). The deployment plan of the beacons is constructed using a software to cover each building location with a range of at least three beacons by limiting each beacon‘s signal strength to 5 m. The software takes an OSM file of a building as an input, estimates the number of beacons required for maximum coverage and outputs the deployment plan (see Fig. 3) of the beacons according to the floor area of a building. The process is repeated for each floor of two buildings. Using the deployment plans, the beacons were mounted on different locations in buildings. If the BLE beacons are relocated due to the alteration of spaces and temporary structures in the dynamic environment, the positions of the beacons in the database file for tagging the locations against each longitude and latitude pair values should be updated accordingly. For acquiring the location coordinates (longitude and latitude pair values) of building users, an Android application (see Fig. 4) is installed in the handheld devices of building users. The application connects with a database containing information about the deployed beacons. In a database, each beacon is identified using its unique identification which corresponds to its assigned building location. As an application launches in a device, it detects the neighboring beacons and selects the best three beacons‘ signals to perform the geo-localization. Based on the received signals‘ strength of the beacons, location coordinates are generated by the application and stored in a document database i.e. Mongodb for further processing. Later, these location coordinates (Fig. 5) are pre-processed in R studio (see Fig. 6). As real-life spatio-temporal data captured from different location acquisition devices very often suffer from noise and interferences because of the environment (Yan and Spaccapietra, 2009). Loss of signals, sensor battery outage and sampling mis-adjustments are

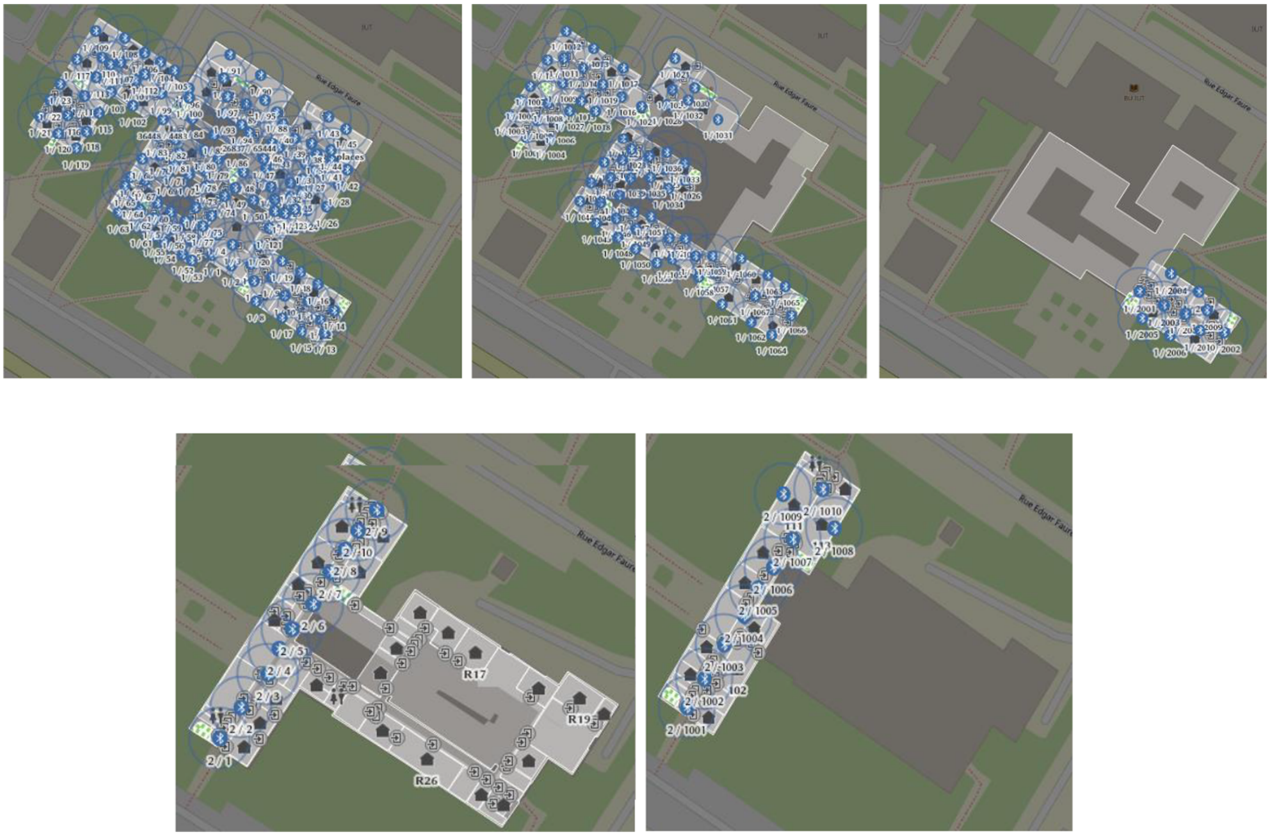

Fig. 3. Deployment maps of BLE beacons of different floors in two buildings.

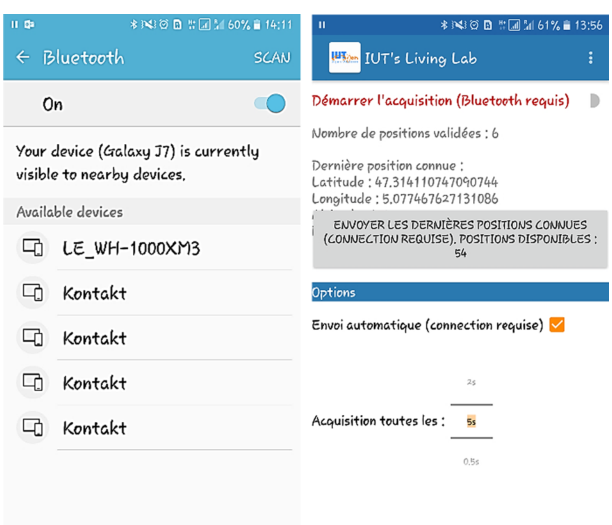

Fig. 4. Mobile application to capture BLE beacons‘ signals.

some of the main reasons for having noisy spatio-temporal data (Zheng, 2015). For reducing the level of noise in the collected data, a median filter is used as it is robust and preferred for datasets having outliers with low deviations (Zheng, 2015).

(2) Tagging locations

For tagging building locations to spatio-temporal trajectories, the ‘STriDE’ is used. Fig. 7 is showing the logical connections between different STriDE model entities, timeslices (TSs), concepts, and user profiles. Here, the STriDE entities (users, trajectories and rooms) are representing the real-world moving and changing objects consisting of unique identifications and evolving spatial and alphanumeric descriptive properties over time. In the model, the objects are defined as the class ‘feature s instances’ which refers to an identification of an object which differentiates it from the other objects (Cruz, 2017). For tagging the semantic information related to the building locations with the TSs, the STriDE model used ontologies which offer the conceptualization of a domain to show relations among different concepts. Here, ‘concepts’ define different building locations as objects having a set of attributes (see Fig. 8). The STriDE model uses an OpenStreetMap building (OSM) file, a taxonomy and a set of rules written in the Resource Description Framework (RDF) language for performing semantic enrichment process. An OSM building file is in the Extensible Markup Language (XML) format that describes vector data for defining room boundaries along with their links with each other. The purpose behind an OSM file is to feed the vector data for describing an entire building structure in the trajectory data model (see Table 4). For labeling and clustering the key-value pairs present in an OSM file, a taxonomy is written as a hierarchy of ‘concepts’ (locations) written as RDF triples using Simple Knowledge Organization System (SKOS) vocabulary. Moreover, a set of rules are created in the form of a JavaScript Object Notation (JSON) file for establishing relations between OSM key-value pairs with the taxonomy. As a result, Java objects (see Fig. 9) having semantic information are generated which are stored in a triplestore (i.e. Stardog) to achieve a complete representation of a building. One important feature of the STriDE model which is responsible for keeping the building evolution for semantic information is that, during the data modeling, the geometry of an object is defined outside the ‘main entity’ (see Fig. 9). Here, an ‘entity’ describes identification of a building location. To store the historical changes occurring during a building evolution, the STriDE data model keeps tracks the spatial, spatial-temporal and filiation relations of building entities (locations and

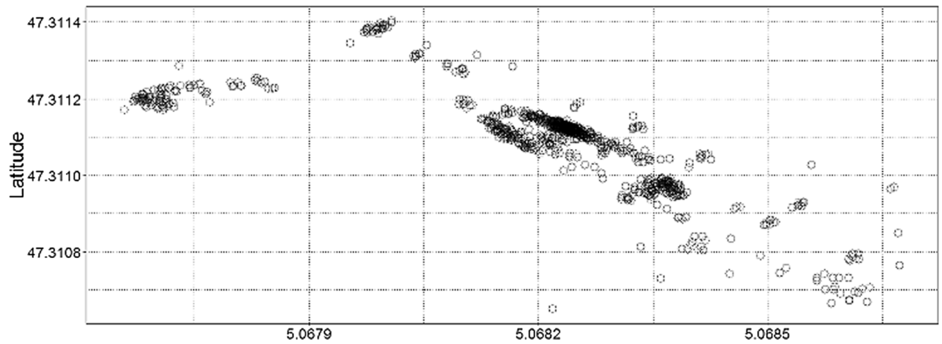

Fig. 5. Raw location data points of a user.

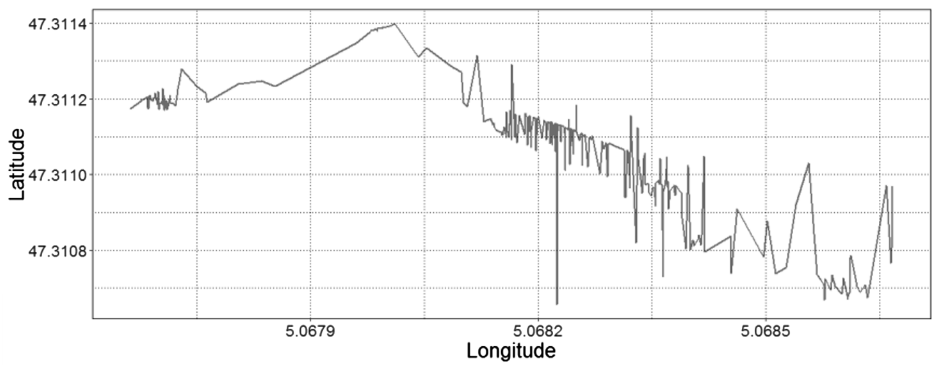

Fig. 6. A filtered spatio-temporal trajectory.

users). The spatial relation holds the information about how a user in a building is related to a reference building location. The spatio-temporal relation tracks how two building locations or a location and a user are linked with each other at the same time.

Moreover, the filiation relation defines how building entities are related by ancestry or successor. It represents the succession links that exist between different representations of the same object at different intervals of time (Harbelot et al., 2015). The STriDE model holds two types of filiation relations which are; continuation (i.e. a change in the building entity but identification (i.e. a room number in case of a location, whereas a profile in case of a building user) is unaffected) and derivation (creation of a new building entity from its parent entity). The STriDE holds the information of these relations with the help of timeslices to keep track the different evolutions (e.g. geometrical and alphanumeric properties of building locations as well as profiles of the users) occurring in a dynamic building environment. A TS is made up of four components which are; an identification, alphanumeric properties, spatial representation and temporal fields (Cruz, 2017). Each TS is valid for a specific time and in case of a change in any of the TS's components except its identification, a new TS is constructed which inherits the properties of the last known state of the object. To illustrate how the STriDE model stores the building evolution with the help of TSs, an example is presented in Fig. 10. A location named 'storage4′ which is a type of a building amenity is divided into two different building rooms which are 'office2′ and 'meeting room3′. The STriDE model uses the 'hasFiliation' link to store this change as shown in Fig. 10. Two different TSs which are; Office2_0 and Meetingroom3_0 are generated for new building entities (Office2 and Meetingroom3) having their geometries and have 'hasfiliation' links with their parent entity i.e. Storage4.

(3) Detecting intrusions

After generating the semantic trajectories (see Fig. 11) using the stored information (see Fig. 9) in the STriDE model users' trajectories are represented as a series of timeslices (see Fig. 12) for detecting intrusions in a building. In our model, as already described above that 'concepts' are defined for tagging building locations with spatio-temporal trajectories. These concepts are defined using SKOS vocabulary and stored in the 'concept scheme'. A concept scheme is a collection of different concepts described as a hierarchy which correspond to different building locations and are stored as triples in the RDF file (see Fig. 8). The purpose of defining a hierarchy is to be more precise about the tagging of a building location. For instance, for recognizing a specific construction site region, we can move towards more exactness to call it as a hazardous zone or a work zone. For achieving user profiling, concepts are used as shown in Fig. 8. Here, a profile is defined as a set of different concepts which a user has access to. For identifying the intrusions, the tagged concepts with the user timeslices are mapped with the allocated concepts according to the user profiles. In this way, unauthorized locations are recognized, and alerts are generated to alert the user and the building supervisors. A triple store query is used for extracting an intrusion from a list of users' timeslices. Fig. 13 is the screenshot of the identified intrusion.

(4) Visualizing intrusions in BIM software

The building in which the experimental set up is done for collecting spatio-temporal trajectories of workers, its BIM model doesn't exist. Eventually, a Revit architectural sample file is used and modified using the information extracted using an OSM file of a building for representing a proof-of-concept integration of systems. Sensors (beacons in our case) are typically not part of a Revit model. For incorporating the sensor data (semantically enriched trajectories) into a BIM model, Dynamo is used. Dynamo works alongside a Revit software requiring an active Revit document having a BIM model and executes a simple execution structure that is; input, process and output (Autodesk, 2017). It means that firstly the relevant building geometry is taken from Revit into a Dynamo, then desired processes are performed using pre-packaged nodes, and finally, the Dynamo outputs the results back into Revit document (Arslan et al., 2019c). Constructing a Dynamo script (also

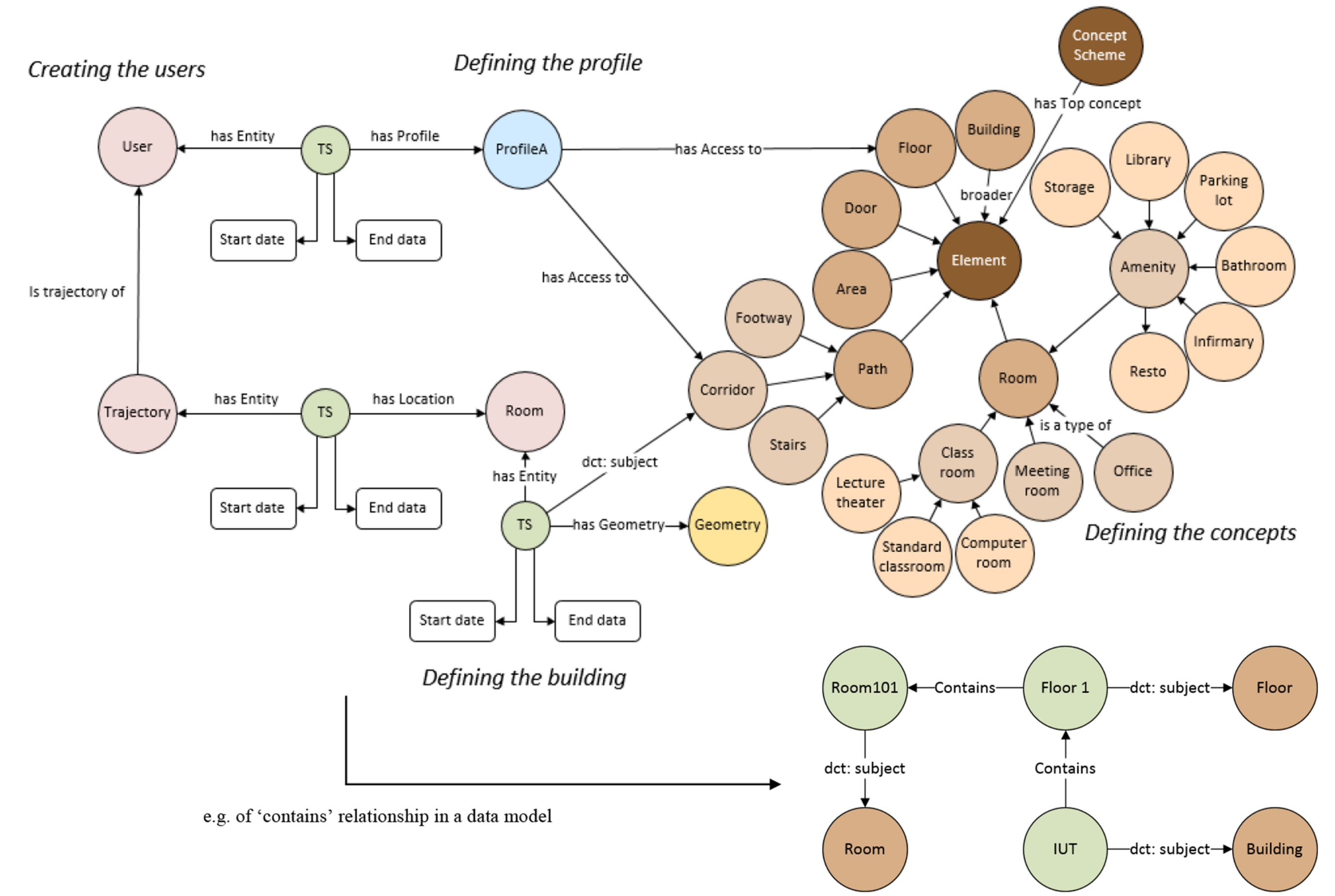

Fig. 7. (a)–(top) The STriDE model (user, trajectory, and room are the entities that may change over time. Whereas, TS is the timeslice and, concepts are defined using SKOS. Each entity is represented using a TS having the start and end dates.) (b)-(bottom) An example of ‘contains’ relationship (The “contains” relation is expressed at the instance level: The Institute of Technology (IUT) contains the 1st floor which contains the Room101).

SPARQL Results (returned in 47 ms)

userName	profileName	concepts
User 1	User profile	Building, Floor, Door, Corridor, Footway, Stairs, Room, Office, Meeting room, Amenity, Bathroom
Maintenance 1	Maintenance profile	Building, Floor, Door, Corridor, Footway, Stairs, Room, Office, Meeting room, Amenity, Bathroom, Storage

Fig. 8. Users and their profiles.

Table 4
Spatial Information to Tag Trajectory Point with a Building Location Extracted from an OSM File.

Location	Room101
Geometry type	Polygon
Location coordinates [longitude, latitude]	([5.068456,47.31081], [5.068349,47.31084], [5.068287,47.31084], [5.068243,47.31082], [5.068198,47.31078], [5.068470, 47.3108])

called a graph) consists of ‘nodes’ and ‘wires’. Nodes are the blocks of code that aim to execute a single discrete function. Whereas, wires are used to connect nodes‘ outputs to nodes‘ inputs for building the data flow from left to right (Autodesk, 2017).

Dynamo graph constructed for the STriDE-BIM integration consists of four key steps (see Fig. 14), which are; (1) all the building locations which are tagged as ‘rooms’ in the BIM model are extracted by defining the category of elements as ‘rooms’ in the Dynamo. A room in the Revit denotes a three-dimensional volume for representing a real building space. Building spaces that need to be identified as individual rooms should be properly bounded by walls before placing ‘room tags’ on them. These tags are called as annotation elements and can be changed manually. Each tagged room in Revit carries a set of parameters such as room number, room name, physical area, etc. that are used for viewing or editing that particular room. In our case, the parameter ‘room name’ will act as a unique identifier for each space for visualizing the problematic room in the Revit model where an intrusion has occurred. The naming convention of Revit rooms is set according to the tagging of

```
stride:W235 a stride:Entity ;
  skos:prefLabel "Corridor of floor 1" ;
  rdfs:comment "" .

stride:GEO-W235-0 a geo:Geometry ;
  geo:asWKT "LINESTRING (20 85, 15 65, 15 50, 20 50, 16 50, 15 15, 20 10, 15 15, 30 15, 30 20, 60 15, 50 15, 50 20)"^^geo:wktLiteral .

stride:W235-0 a stride:TimeSlice ;
  stride:hasStartDate "2019-02-01T00:00:00"^^xsd:dateTime ;
  stride:hasFeature stride:W235 ;
  geo:hasGeometry stride:GEO-W235-0 ;
  dct:subject stride:Corridor ;
  stride:hasEndDate "9999-12-31T23:59:59"^^xsd:dateTime .
```

Fig. 9. Parsed OSM file using the semantic rules and the taxonomy (The script is the RDF Turtle definition of an object of the kind "Corridor" identified by the value stride: W235).

semantic locations as described in the STriDE model. (2) After extracting the list carrying room names of the building, the details of occurrence of intrusions i.e. intruder ID, time of occurrence of intrusion and room name where the intrusions are detected are imported into Dynamo. This is achieved by calling an API to output the result from the STriDE model automatically in the form of an Excel sheet containing the details of occurred intrusions. (3) On receiving room's data from an active Revit document and intrusions' data taken from the STriDE model, the room location where an intrusion has occurred is highlighted in 'Red' color in a BIM model using the mapping of room names in both lists (see Fig. 15). The change in the color of the Revit room is done using the 'Element: OverrideColorInView' node. This node changes the color of the Revit element (room in our case) in the active view irrespective of the current element display properties. (4) As soon as the problematic room is highlighted in the Revit, this process invokes another user window to ask for details of the intrusion occurred in a specific room location. After inputting the desired room name, time of occurrence of the intrusion in the particular room and its corresponding intruder ID will be displayed to the user in the Revit software.

4. Discussion

The proposed system integrates the output of the STriDE model with the BIM software for displaying intrusion information to building supervisors and H&S managers for safety management. The developed system is validated using a real-life IPS feed of the building users extracted from BLE beacons. BLE beacons originally provide proximity-based services and coarse-grained location positioning for indoor application scenarios (Paek et al., 2016). It should be noted that proximity

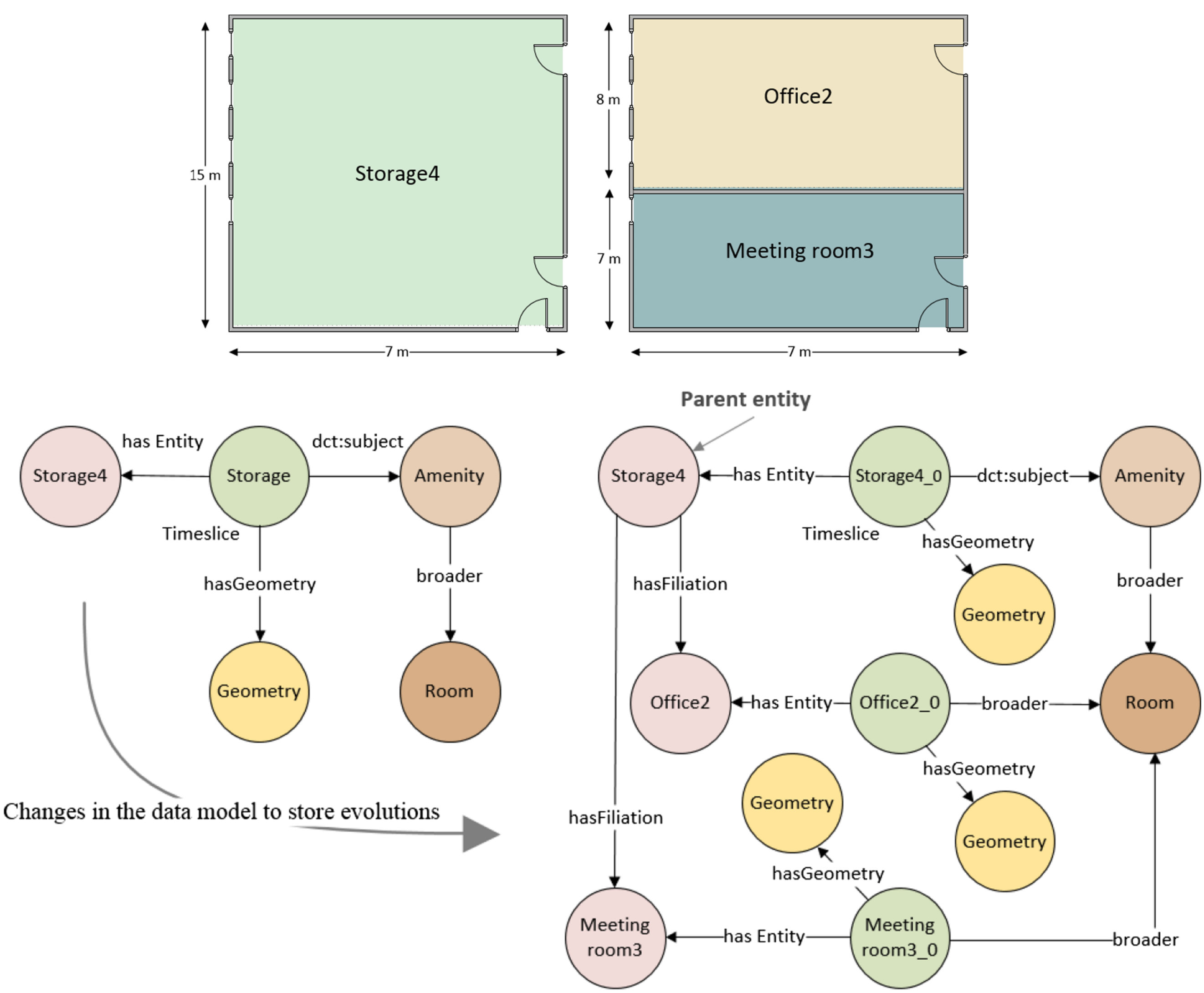

Fig. 10. Storing the dynamicity of a building environment.

traj	userName	location
stride:TrajOfWorker2-1	Worker 2	Outdoor pathway
stride:TrajOfWorker2-2	Worker 2	Storage room
stride:TrajOfWorker1-1	Worker 1	Outdoor pathway
stride:TrajOfWorker1-2	Worker 1	Corridor of floor 0
stride:TrajOfWorker1-3	Worker 1	Office 1
stride:TrajOfWorker1-4	Worker 1	Corridor of floor 0
stride:TrajOfWorker1-5	Worker 1	Outdoor pathway
stride:TrajOfWorker1-6	Worker 1	Storage room

Fig. 11. Trajectories database having time slices of two different users.

s	p	o
stride:TrajOfWorker1-3	rdf:type	stride:TimeSlice
stride:TrajOfWorker1-3	stride:hasStartDate	2018-01-02T09:06:00
stride:TrajOfWorker1-3	stride:hasEntity	stride:TrajOfWorker1
stride:TrajOfWorker1-3	stride:hasEndDate	2018-01-02T09:30:00
stride:TrajOfWorker1-3	stride:isTrajectoryOf	stride:Worker1
stride:TrajOfWorker1-3	stride:hasLocation	stride:W5

Fig. 12. Timeslice description of a Worker1 trajectory.

userName	room	roomLabel	start	end
Worker 1	stride:W1002	Storage room	2018-01-02T09:36:00	9999-12-31T23:59:59

Fig. 13. Detecting an intrusion from trajectory's timeslices.

(i.e. being close to a specific object) is correlated to the building location (i.e. exactly where a person is) but it is not necessarily the same. A precise building location which corresponds to an absolute value of the coordinate system (e.g. longitude and latitude values) is more than just proximity. The signal strength readings of BLE beacons fluctuate significantly over the environmental (e.g. physical obstacles, walls and ceilings causing the multipath effects), mobile platforms (e.g. hardware and software technological aspects) and deployment factors (i.e. location, more specifically the height of installed beacons from the ground) (Paek et al., 2016; Ke et al., 2018). These external factors introduce variations in the signal strength readings of beacons caused by the propagation diffraction, reflection and scattering which naturally complicates the process of determining the precise location information of objects in real environments (Ke et al., 2018).

The process of determining the precise proximity data of building users gets more complicated as the system resolution for intended analysis increases. The overall system resolution is defined using spatial, temporal and occupancy resolutions. As the resolution of the deployed sensors increases, the building spaces get smaller, the semantic information corresponding to the building locations gets more specific, building users get more identifiable individually and eventually, their activities can be inferred. For developing the proposed system, the system resolution that is targeted is highlighted in Yellow color[1] in Fig. 16.

As it can be observed from Fig. 7 that the developed system holds the information at room level that is collected per second using beacons for identifying each building user using its unique identification to execute an intrusion detection system. For keeping track the semantic information of rooms, the information of their interconnectivity along with their alphanumeric properties is described using an OSM file, user-defined rules and a set of taxonomies. After defining the desired system resolutions, a set of tests were performed as described in the next section for understanding different attenuation effects of BLE signals in the building environment for precise proximity data collection of building users.

4.1. Measurement data analysis for better accuracy in identifying the building locations

The effectiveness of a developed system in detecting intrusions

[1] For interpretation of color in Fig. 16, the reader is referred to the web version of this article.

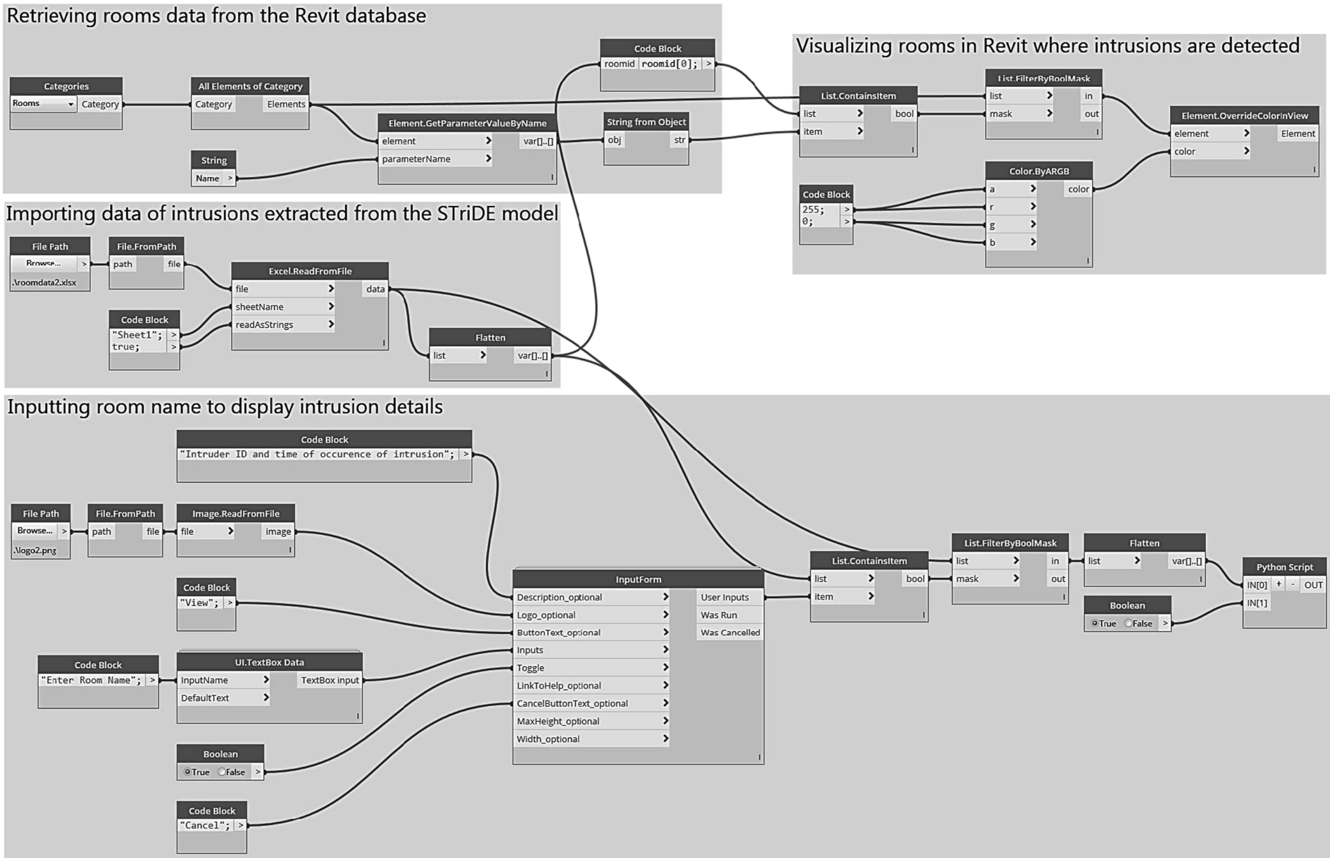

Fig. 14. Graph in Dynamo for visualizing intrusions.

using spatio-temporal trajectories of users is completely dependent on the identification of the accurate building locations using BLE beacons. The environment varies in buildings because of a different material of walls, the density of users, and type of equipment present inside a building (Paek et al., 2016; Ke et al., 2018). The environmental factors of a building affect the Received Signal Strength Indicator (RSSI) values of beacons in identifying the precise locations of building users. To understand the building environment for deploying the beacons for achieving higher detectable RSSI values of beacons in the coverage areas, three different tests were performed which are described in Table 5.

For the 1st test, a beacon is mounted at 1.2 m-height (see Fig. 17) and its RSSI values are recorded per second. The reason for selecting the height of 1.2 m is to keep the height of a beacon identical at which the building users hold their handheld devices (Paek et al., 2016). In addition, the alignment of a beacon is adjusted to face it towards the position of a handheld device so that line-of-sight (LOS) communication is possible. By configuring the transmission power of a beacon, it is made detectable at the distance of 5 m. Using the settings mentioned above, an Android-based mobile application is used for detecting the beacon signals and recording its RSSI values per second while the distance between a beacon and a handheld device is kept constant i.e. 2 m. However, this distance can be varied until the maximum distance where a beacon is detectable by a handheld device. Then, by keeping the same height, time duration and a beacon configuration, a beacon is dropped from the wall to the ground and then mounted it back to its original position for visualizing the amount of degradation in the RSSI values. The RSSI is measured in dBm indicating the signal strength of a beacon and used for proximity analysis. The RSSI value of a beacon degrades as distance increases. The lower negative RSSI value in dBm shows the closeness of a beacon to a handheld device that is configured for detecting beacons (Paek et al., 2016).

As it can be seen from Fig. 18 that a signal strength of approximately −25 dBm is decreased when a beacon is dropped on the ground. The reason for decreased RSSI values is not only the falling off the beacon but also the interference caused by the user‘s body who made a beacon to fall as it absorbs radiofrequency radiations. There will an obvious frequent case of falling off the beacons from their original mounting positions from the walls in dynamic building environments. The circumstances of falling off the beacons should have minimal effect on the RSSI values of the beacons for maintaining the required coverage area. Existing literature shows that signal smoothing techniques involving different filters (mean, median and Kalman) can be applied for reducing the effect of huge spikes and dips in the reported RSSI values (Zheng, 2015). The signal smoothing techniques are based on averaging algorithms which prevent the situations in the collected data where a beacon has reported a signal of −85 dBm and then it jumps the second to −60 dBm. For our study, a median filter is used on the data to smooth the signals as it is efficient and robust in eliminating the outliers of lower deviations (see Fig. 18). However, advanced filters such as Kalman filter can also be applied as per the requirements and the degree of deviations in measured signals. For the 2nd test, a beacon is mounted in a room and its RSSI values are collected from inside the room (see Fig. 19a. Later, to study the effect of a dynamic environment where walls are often added in the building infrastructure. For this, a wall is included in the area (i.e. Area24 consisting of a Room101 and a Corridor) covered by a beacon that is defined in the system for recognizing a particular building location. A beacon is placed outside the room in the corridor (see Fig. 19b. Whereas, a room and a corridor belonging to the same location (i.e. Area24) defined in a data model. The RSSI values of a beacon mounted in a corridor are collected (see Fig. 20) from inside the room to study the effect of the wall on a beacon.

As shown in Table 6, there is a reduction in the signal strength of around −12 dBm because of the interference caused by the wall.

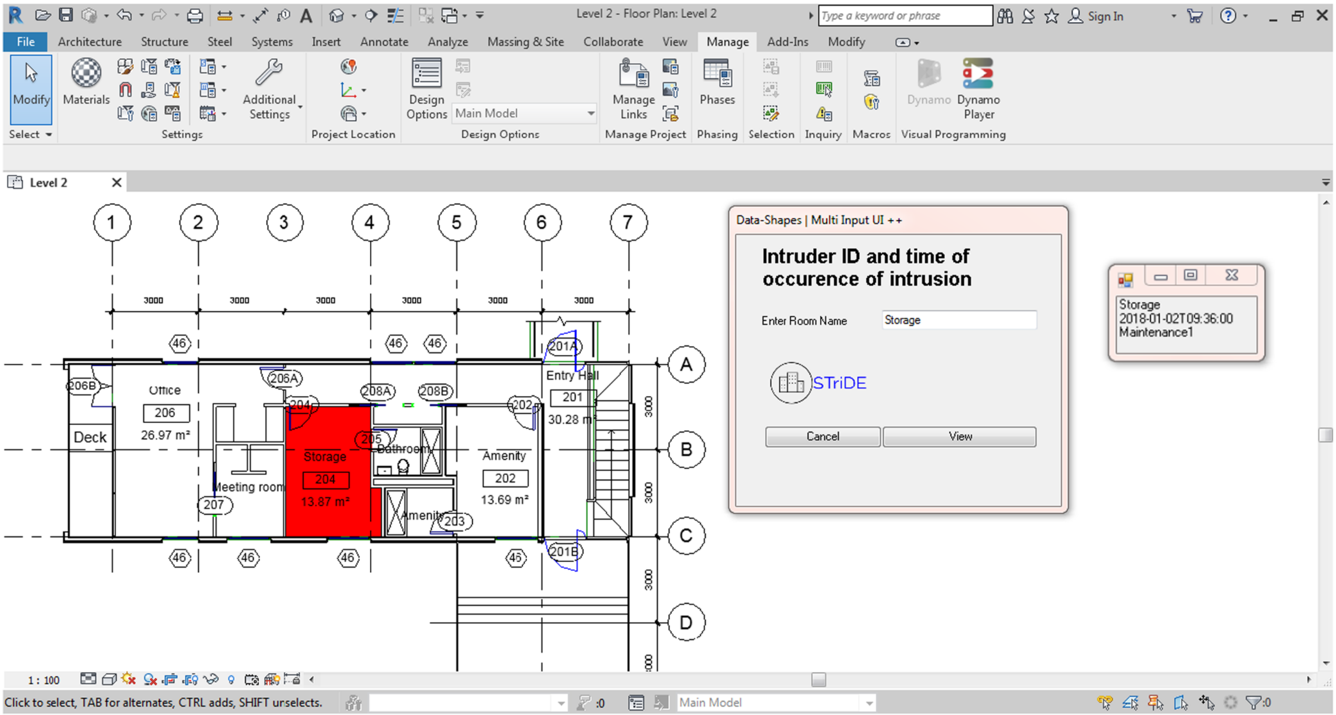

Fig. 15. Visualizing intrusion information in Autodesk Revit software.

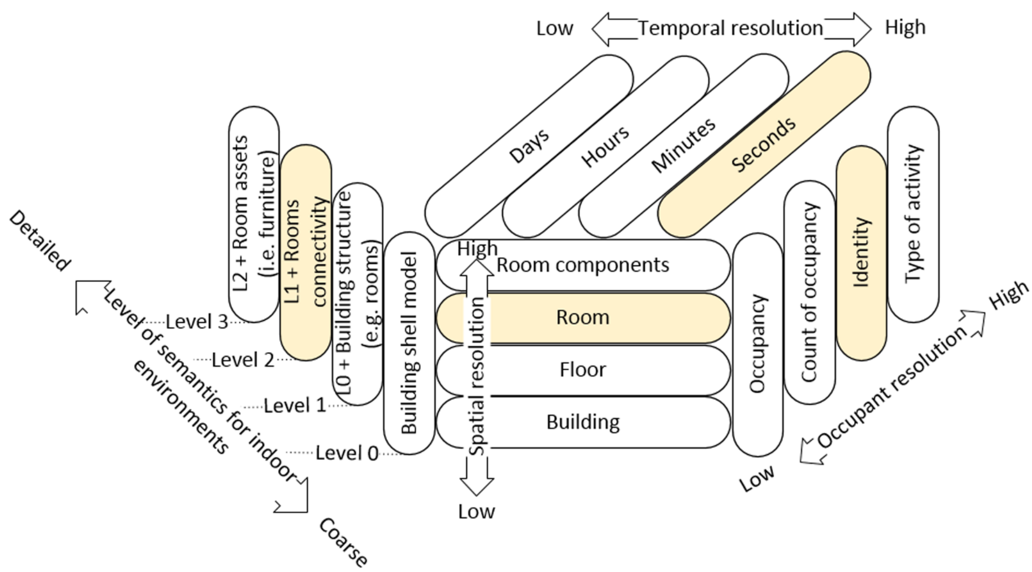

Fig. 16. Level of spatial, temporal and occupant resolution targeted for the semantic enrichment of spatio-temporal trajectories (Open Geospatial 2018; Pittarello and De Faveri, 2006; Tang et al., 2018).

Table 5
Tests.

Test	Purpose	Strategy
1	Understanding the degradation effect of the RSSI values in case of falling off the beacons from the wall	Dropping a beacon from the height of the wall
2	Simulating the concept of a dynamic building environment where the walls and infrastructure supports are added in building areas	Mounting a beacon in a corridor and detecting its RSSI values inside the room to study the effect of the wall on a beacon
3	Studying the effect of the existence of beacons tagged with two interconnected adjacent building locations for determining the correct location in a dynamic environment	Mounting a beacon in a room and another beacon in a corridor and understanding the variation in the RSSI strength of both the beacons as the user moves across these locations

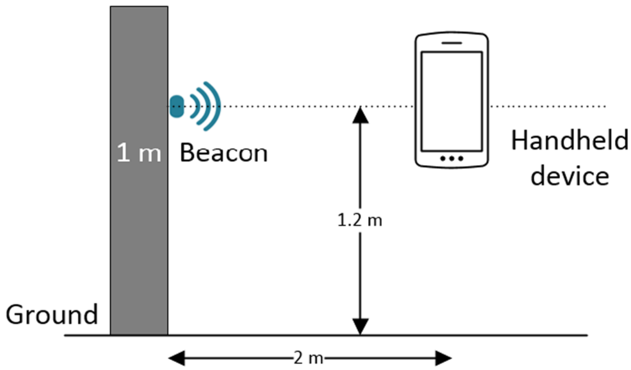

Fig. 17. Mounting a beacon at 1.2 m-height.

For the last test to visualize the effect of the existence of beacons tagged with two interconnected adjacent building locations for determining the correct location in a dynamic environment. A beacon is mounted in a room named ‘Room101′ whereas, another beacon is mounted in a corridor. The transmission power of these beacons is configured in a way that two beacons are detectable in their neighboring locations. For RSSI data collection, a user with a handheld device moves away from ‘Room101′ towards a corridor approximately 1-m distance every second. The test is depicted in Fig. 21

As it can be seen from Fig. 22 that when a user moves from ‘room101′ to a ‘corridor’, the RSSI values of both beacons’ variates. Initially while at room101, the room‘s beacon shows the stronger RSSI strength. As a user comes near the door and walks across the door connecting these two locations, the RSSI value of a room‘s beacon starts getting degraded. As the user approaches near the corridor‘s beacon, the signal strength of both the beacons gets inverted. Here, a point that is critical to understand is the effect of obstacles on the RSSI of beacons. The user stops its movements in a corridor from the same distance where a user has started its movement in a room i.e. 2 m. The RSSI values of both beacons at a 2 m distance should be nearly identically but that is not the case in Fig. 22. The reason of a lower RSSI value in a room is because of the deployment of other electronic equipment operating that must be interfering with the BLE signals as well as the presence of people who absorbs the radiofrequency radiations (Paek et al., 2016). While in a corridor, the closed space introduces the scattering effect in beacon‘s signal which ultimately increases the RSSI value of a corridor‘s beacon.

The conclusion that is perceived from this test is that the existence of multiple beacons across different building locations does not affect in collecting the strongest RSSI values for detecting the most precise building locations of a user. However, collisions may occur if the material of walls is not dense enough which introduces the effect of attenuation in the RSSI signals. For our case study as shown in Fig. 22, the change of locations can be observed clearly while analyzing the RSSI values of beacons. This will eventually help us to collect precise proximity data of building users.

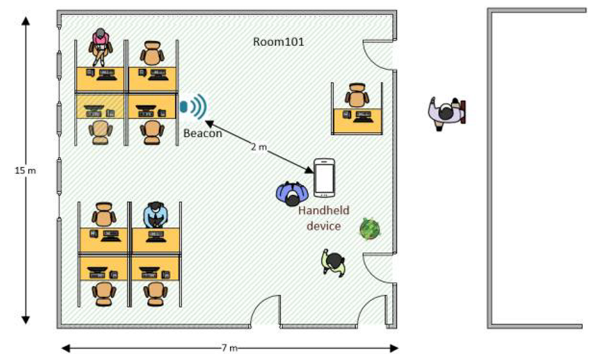

Fig. 19a. No effect of an obstacle.

4.2. Strategy employed for a precise location identification

The approach that is used for reducing the proximity errors (resulted from the scenarios of test 2 and 3 as discussed above) due to the obstacles in our study is to first capture data values in shorter time intervals and then applying the K-means clustering algorithm (Žalik, 2008) to identify the precise building location by computing the central points of the users in collected data values (see Fig. 23). The purpose of using this approach is to take a mean of location coordinates of detected locations than just relying on a signal beacon reading for identifying a building location. The central points of the user movements are later mapped with geographical coordinates of the building locations extracted from the OSM file to calculate the accuracy in recognizing the building areas where the users are present. The application of the K-means clustering algorithm along with smoothing technique has enabled us to achieve high location tagging accuracy.

4.3. Accuracy of location identification for intrusion detection

Using the geographical information of building structures extracted from the OSM files, the deployment maps of the beacons were generated. However, a BIM file can also be used for designing and optimization of the beacon‘ deployment plans. An OSM file is utilized because of its compatibility with software used for constructing the beacons‘ deployment plans. Table 7 reports some details of spatio-temporal data used for our experimentation.

Approximately 8426 location points of 11 building users are collected using BLE beacons during different intervals in 2 weeks with a sampling frequency of 5 s. Then, our semantic enrichment system is used to transform the spatio-temporal trajectories into semantic trajectories by incorporating the contextual information about the building. The accuracy in tagging the building locations identified from the processed trajectories with the information residing in our data model was around 90% (see Table 8). Some of the building locations were not labeled correctly because of indoor interferences caused by the building objects which generated inaccurate recognition of the building locations using BLE beacons.

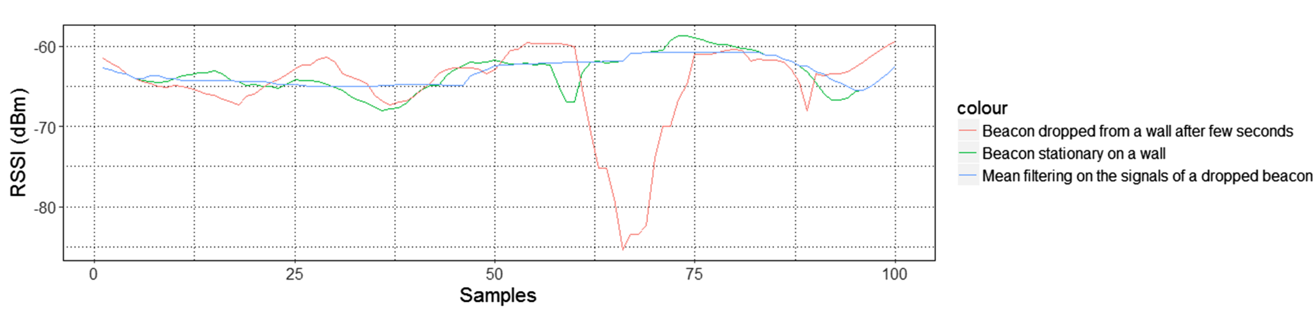

Fig. 18. Effect of falling off a beacon.

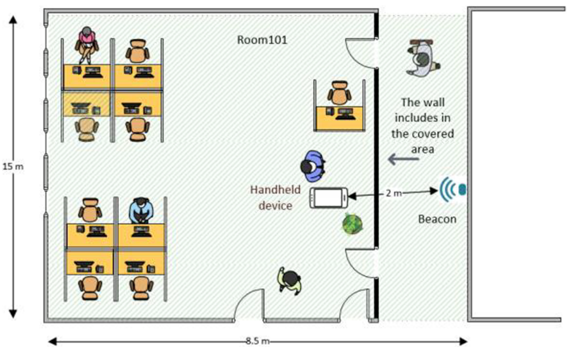

Fig. 19b. Effect of a wall on RSSI of a beacon.

Here, the tagged building locations refer to the accuracy of spatially joining (i.e. $Trajectorypoint_{\theta}Region$) the geographical coordinates of a user with the building information stored in the form of majorly as polygons using a set of geographical coordinates (longitude and latitude pair values) extracted from an OSM file of a building (see Table 4). Here, a parameter 'θ' is based on the topological spatial relation (e.g. distance). After computing the θ, spatial joins are performed with the centroid of user locations to extract the precise building location. More details on the spatial joins can be found in (Yan, 2011) research.

4.4. Analyzing the positioning errors

To find out the errors in the dataset collected from the BLE beacons which eventually caused the detection of false intrusions of users in a building. The queries are executed for identifying certain movements of the users which are not correctly acquired by the system (see Fig. 24). For example, at a time $t = 1$, a user is detected in Room1. Whereas, at $t = 2$ a user is in Room2. However, these two rooms are not connected as can be observed using a BIM model. By bearing in mind the sampling interval (i.e. 5 s) of a trajectory data, it is not possible to have such quick movement of a user between two locations which are not connected. For instance, a user moved from Room1 to Room2. Just for the sake of keeping an explanation simple for an example, 'days' are used as start and end dates of the timeslices. However, in our system start and end dates contain the precise date and time values. Using the trajectory data of a user, we know that, a user moved on Wednesday (as stated by the end day of the 1st timeslice (i.e. TS_{T1}) and the start day of the second timeslice (i.e. TS_{T2}). For verifying the validity of this user movement, we need to find out the states of the rooms (Room1 and Room2) at the time of movement (i.e. somewhere on Wednesday). Here, a term 'state' refers to a timeslice holding an identification, alphanumeric properties, spatial representation and temporal fields. At the occurrence of the changes in the alphanumeric and spatial (geometrical) properties of an entity (i.e. room), a new timeslice is created. For verifying the two connected timeslices, the end day of a timeslice should be the start day of the succeeding timeslice of a room. For tracking, we will check each generated timeslice of the rooms for finding the one for which the Wednesday is between the start and the end day. For Room2, it's easy to check as we have only one timeslice starting on Monday (see Fig. 25). To verify the connectivity of Room2 with a Room1, we will analyze the series of generated timeslices of Room1. For Room1, we can see that the 1st timeslice (TS_{R1}) starts on Monday and ends on Friday. Whereas, the 2nd timeslice ($TS_{R1'}$) which is resulted by the change in the geometry of a room starts on Friday. The day of movement which was 'Wednesday' is between Monday and Friday has no concern with the 2nd timeslice (i.e. $TS_{R1'}$) as this timeslice starts from Friday. From here, we came to know that the movement is done from the 1st timeslice (i.e. TS_{R1}) on Wednesday to Room2, eventually generating a timeslice TS_{R2}. But, a timeslice TS_{R1} of Room1 is not directly connected with a timeslice TS_{R2} of Room2 as shown in Fig. 25. It means that initially Room1 was not connected with Room2. Over time, the geometry of the Room1 is changed (generating a new timeslice i.e. $TS_{R1'}$) which might be the result of the construction of a new door or a pathway between Room1 and Room2. This change in the geometry made Room1 connected with Room2 in the system. However, this was not the case in the observed trajectory data as the movement is made from TS_{R1} which is not possible. So, it's an error. See Fig. 26 to see some of the errors. The errors in our system can be majorly caused because of the below reasons;

- Stopping the mobile application at a certain location and restarting it from another location can transmit the trajectory point of the previous location. This is usually caused by a delay in the detection and the transmission of a collected trajectory point.
- Some of the beacons might have fallen from their actual locations. The beacons were later tagged to the wrong places and can potentially cause errors during the trajectory data collection.
- The geometries of the locations because of the new construction works are not fully incorporated in the model. This might be the reason of incorrect tagging for the locations to the trajectories by our system.

However, for our scenario that is built for an already constructed building, the incorrect location tagging (see Fig. 26) in the trajectories resulted because of the former two reasons.

5. Conclusion and future work

BBS trainings have a potential for reducing near-miss incidents such as intrusions on the construction sites by educating the workers and increasing their safety awareness about the dynamic nature of construction job environments. However, BBS trainings completely depend on the manual procedures executed by the experienced building supervisors. Also, it lacks timely feedback, and an assessment of the occurrence of intrusions for further construction operations. To overcome this limitation, intrusion detection systems based on different sensor-based technologies are developed in the existing literature. However, these systems cannot recognize intrusions in dynamic environments where the building locations evolve over time. This opens many data

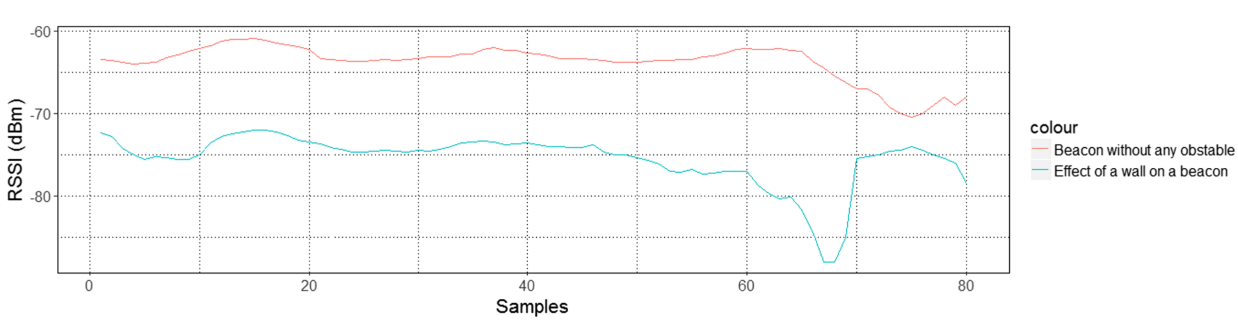

Fig. 20. RSSI plot to see the effect of a building obstacle (i.e. wall) on beacon.

Table 6
Effect of a Wall on RSSI Values.

No.	Cases	Average RSSI value (dBm)
1	Beacon without any obstacle at a distance of 2 m and height of 1.2 m	−63.77
2	Beacon affected by a wall at a distance of 2 m and height of 1.2 m	−75.54

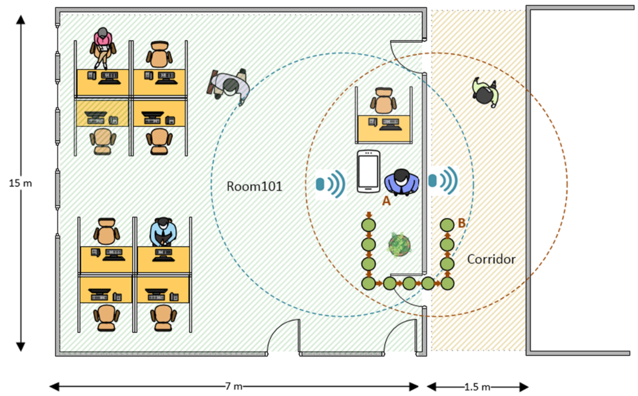

Fig. 21. RSSI measurement path in a dynamic environment.

management challenges for keeping track the changes in the contextual and spatial information associated with the locations which evolve over time for identifying intrusions from the perspective of the building or site environment.

The main contribution of this study was the development of an intrusion detection system based on a data model which can track the building spatial and contextual evolutions over time using spatial-temporal and filiation relationships among building entities (users and locations). Using BLE beacons, movements of building users having different profiles in 2 weeks are recorded in a batch mode. Later, the movements are processed and enriched with their associated building locations using an OSM file. An OSM file has provided the geographical coordinates of the buildings. This geographical information is used for deploying the beacons in buildings and defining the building locations in a data model. However, a BIM file can also be used for beacon planning, deployment, and retrieval of building infrastructural information. But the system is implemented using an OSM file as BIM files of the buildings where the experimentations are conducted do not exist. However, the output of the developed system is integrated with the BIM software to visualize the building locations where the intrusions have occurred. In the literature, there exists many 3-dimensional Computer Aided Design (CAD) software for generating the building visualizations for different built environment applications. Though, BIM approach is chosen as it enhances the inter-organizational collaboration of information among project members because it is based on the Industry Foundation Classes (IFC) standard that is universal and supports easy and fast information exchanges.

Nevertheless, the BIM approach provides countless benefits to Architecture, Engineering and Construction (AEC) industry by

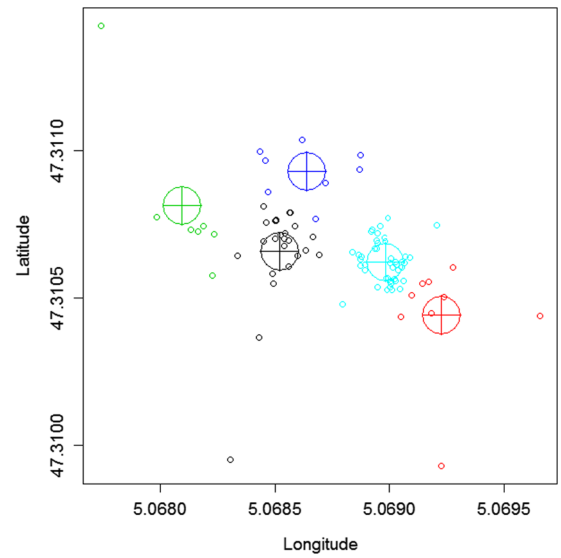

Fig. 23. Calculating centroids of user movements for precise location identification.

Table 7
Trajectory dataset.

Dataset	No. of users	No. of IPS records	Tracking time	Sampling frequency
Building users	11	8,426	2 weeks	5 s

Table 8
Developed system accuracy for Identifying Intrusions.

Detected user locations	Correctly tagged building locations	System Accuracy
150	136	90%

providing a centralized platform to store digital models of buildings. BIM-based n-dimensional digital models hold the updated information of buildings. Once the building model is modified by the AEC managers as the construction work progresses, the previous information of building is tracked using the IFC files. However, the historical BIM information needs to be integrated with the real-time trajectory data of building users so that different behaviors of building entities (users and equipment) can be studied in detail concerning the type of changes

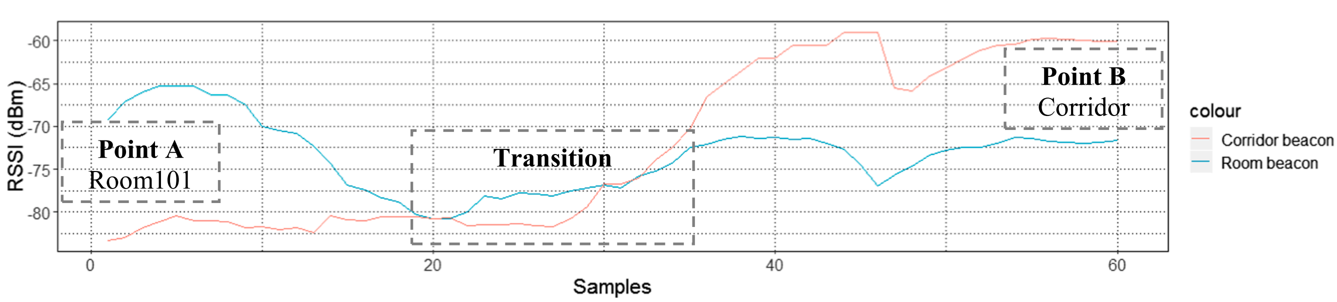

Fig. 22. RSSI measurement while a user moves from a point A to point B.

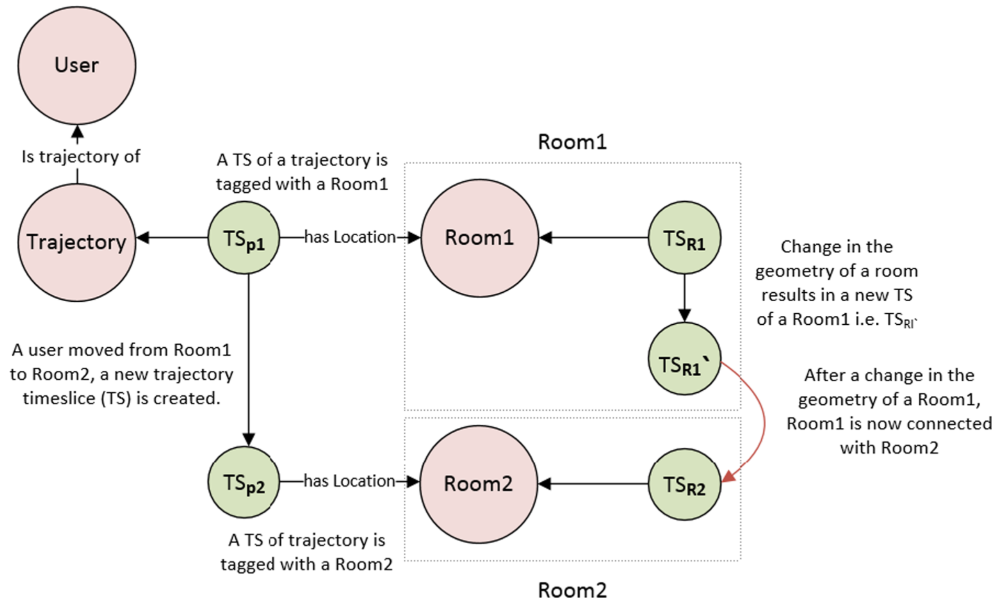

Fig. 24. A scenario for extracting the positioning errors.

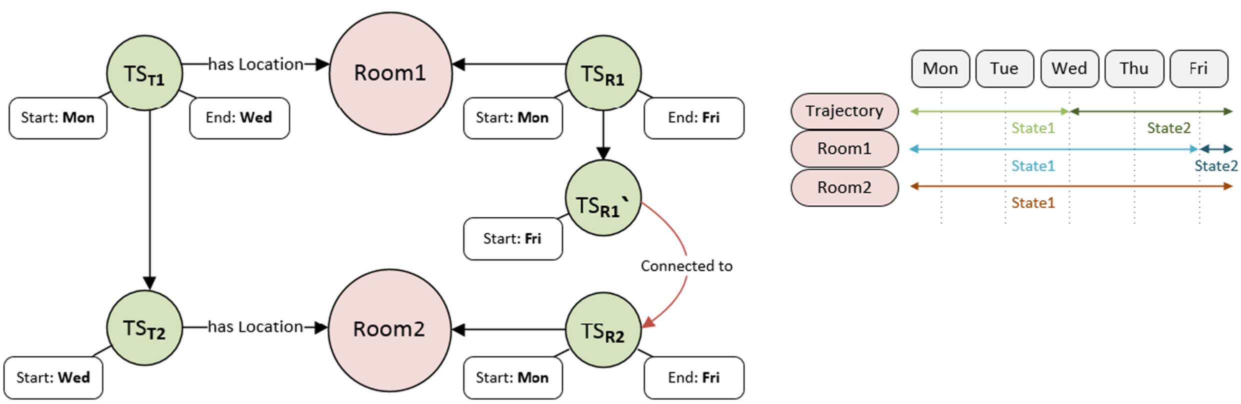

Fig. 25. An example of a scenario for extracting the positioning errors.

SPARQL Results (returned in 1828 ms)

user	from	to
stride:b1bb9e247f060f5e	stride:W265	stride:W206
stride:b1bb9e247f060f5e	stride:W206	stride:W22
stride:b1bb9e247f060f5e	stride:W22	stride:W242
stride:b1bb9e247f060f5e	stride:W242	stride:W22
stride:b1bb9e247f060f5e	stride:W22	stride:W105

Fig. 26. Positioning errors showing user movements between not-connected locations.

occurred in the building environment. To add this functionality in the BIM software, a prototype system is developed which functions as an Autodesk Revit (BIM software) plug-in by adding the functionality of historicization of real-time user trajectory data contextually mapped with the information of buildings. Also, with the help of user profiling, intrusions are visualized on a BIM software using BLE beacons for safety management. The developed system can not only help building supervisors and H&S managers for detecting intrusions to avoid unsafe situations in dynamic building environments such as construction job sites but will also provide a centralized data repository for storing all trajectories generated from the users movements taken place on the construction site for future movement-related behaviors analysis. One of the limitations of the presented study is that the building information is extracted using an OSM file for feeding into a data model for achieving the historicization of buildings. However, BIM model should be utilized for all the building-related processes which include sensor placements in buildings and spatial information mapping with the user locations extracted from BLE beacons. Moreover, the developed system should be made synchronized with the updates occurring in the BIM model in real-time for maintaining the historicization of building information by tracking the spatial and contextual evolutions in dynamic construction environments. Furthermore, at present, the prototype system is implemented in already constructed buildings. Further work is required to empirically test the functionality of the developed system on real construction sites to understand the unsafe behaviors of workers to reduce safety-related accidents in buildings.

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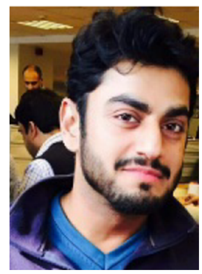

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