Identifying Intrusions in Dynamic Environments using Semantic Trajectories and BIM for Worker Safety

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Abstract. While there exist many systems in the literature for detecting unsafe behaviors of workers in buildings such as staying-in or stepping into unauthorized locations called intrusions using spatio-temporal data. None of the current approaches offer a mechanism for detecting intrusions from the perspective of a dynamic environment where the building locations evolve over time. A spatio-temporal data model that is required to store worker trajectories should have a capability to track a building evolution and seamlessly handles the enrichment of stored trajectories with the relevant geographical and application-specific information sources for studying the worker behaviors using a building or a construction site context. To address this requirement of maintaining the information which is generated during the building evolution and for constructing semantically enriched worker trajectories using the stored building information. This work reports a system which offers the ability to perform user profiling for detecting intrusions in dynamic environments using semantic trajectories. Later, Building Information Modeling (BIM) approach is used for visualizing the intrusions from a standpoint of a building environment so that necessary actions can be performed proactively by the safety managers to avoid unsafe situations in buildings.

Keywords: Intrusions, Behaviors, Safety, Construction, BIM.

Introduction

Intrusions are unauthorized stays or walking through the hazardous areas and are very common type of near-miss incidents occur frequently on the construction sites [1, 2]. According to the Health and Safety Executive (HSE) UK, near-miss incidents such as intrusions are one of the major reasons of the construction accidents which often result in falling from heights, electric shocks, caught in or between, and being struck by the construction machinery [3]. Intrusions on sites are often ignored as current construction safety assessment methods are mainly focused on visible consequences such as injuries or deaths [1, 2]. For monitoring the intrusions, real-time safety monitoring solutions containing Information and Communication Technologies (ICTs) are employed on the construction sites for safety management [4]. Spatio-temporal datasets [5] collected from the Global Positioning System (GPS) or Indoor Positioning System (IPS)-based systems have been used extensively to understand the mobility dynamics of moving objects [6]. A raw spatio-temporal dataset consists of ordered sequences of discrete-time triples in the form of ⟨latitude, longitude, timestamp⟩ known as trajectories [5]. Though, additional contextual information [7] is required to make raw trajectories more meaningful for supporting advanced trajectory applications [5]. The additional pieces of contextual and application information are called annotations [7] which are acquired from various external data sources such as web-based repositories and geographical information systems. The process of tagging annotations to a small segment of a trajectory or a complete trajectory is known as semantic enrichment [5]. Enriching raw trajectories with the semantics of space (e.g. the physical location, where a trajectory was generated), and the semantics of time (e.g. time interval having a start and stop timestamps) give more meaning in discovering behaviors to study movement dynamics of people and moving objects [7]. Eventually, state-of-the-art 3D-visualization approaches such as BIM can be used for visualizing the unsafe behaviors [8] for identifying occurrences of intrusions on sites from a perspective of the building environment for better safety planning and access control.

The rest of the paper is organized as follows: Section 2 describes the background of the study. Section 3 is based on the proposed prototype system. Section 4 presents the discussion, a conclusion and an outlook of the future work.

Background

In this section, a brief review [9-15] is presented on the existing solutions developed for tracking construction workers to prevent near-miss incidents such as intrusions on sites for safety management. A study [9] presented by Naticchia et al. is one of the most appropriate examples of detecting intrusions on construction sites using wireless communication technology. As intrusions typically involve such untrained workers who carry out construction activities without having an appropriate awareness on carrying out works inside the hazardous areas on sites such as confined spaces which ultimately pose great threats to the construction safety. A framework [10] based on deep learning method uses the images of the workers obtained from the videos for capturing their identifications and verifies whether an on-going work is being carried by the certified workers or not. A similar study [11] based on virtual fencing logic using ultra-wideband technology is demonstrated for preventing construction workers from accessing predefined hazardous zones. The system also generates alerts in real-time if the safety risk level to access the hazardous zone increases. Existing literature also includes safety monitoring systems which are developed based on the requirements acquired from the historical records of accidents for further preventing the near-miss incidents. An example of such systems [12] in which information requirements for preventing struck-by-falling-object accidents are collected and a system is built using ZigBee-Radio Frequency Identification (RFID) sensor network for tracking workers and materials on sites. Moreover, Fang et al. [13] designed a system mainly for indoor localization to monitor construction sites for worker safety. Another similar ZigBee-RFID-based study [14] is present in the literature for tracking identity information of workers. The system is developed after analyzing historic case-studies concerning near-miss accidents. Apart from outdoor and indoor safety systems for reducing near-miss incidents on construction sites, there also exist solutions for preventing accidents in underground construction scenarios. Ding et al. [15] described a study in an underground metro tunnel construction setting based on Fiber Bragg grating (FBG) sensor system and an RFID. Their system determines if workers are working in such locations, which can become hazardous with time as the nature of locations is changing as construction work progresses. Analyzing such risky locations in real-time with environmental monitoring sensors can help to generate timely warnings to safety managers for preventing accidents.

After reviewing the above safety solutions for minimizing the intrusions, it was concluded that the existing systems are intended for recognizing the intrusions where the building locations are treated as static entities and do not involve over time. However, in case of dynamic environments such as construction sites, locations evolve in geometry (shape and size) or attributes (alphanumeric semantic information) with time as construction works progress. These building evolutions introduce data management challenges for storing worker trajectories and annotating them with the most updated building information. To address this data modeling requirement for storing trajectory data captured from the dynamic environments such as construction sites, initially existing spatio-temporal trajectory data modeling approaches [16, 17] are reviewed. Literature [16] suggested that ontology-based modeling approaches represent semantic trajectories with richer semantic information related to location and time by integrating different types of information enrichment processes as compared to the other approaches. In these models, initially, segmentation approaches are used to output the structured trajectory episodes. Later, these trajectory episodes are mapped on ontologies for annotating them with relevant Point of Interest (POI) information. In addition, 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 an 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. More details on the present semantic trajectory modeling approaches can be found in [16-19]. Therefore, an ontology-based modeling approach is used for developing our prototype system.

Intrusion Detection System for Dynamic Environments

To address the research gaps identified in the previous section, an intrusion detection system is presented for dynamic environments using semantic trajectories and an open-sourced BIM platform. The developed system has the ability to keep track of the dynamically changing locations for constructing semantic trajectories to understand the user behaviors. The developed prototype system focuses on the following;

4.1 Data Preprocessing and Semantic Enrichment

To detect intrusions using spatio-temporal trajectories, location data of users is acquired after installing 200 Bluetooth beacons in a building. For collecting the location coordinates (longitude and latitude) of the users, an application is developed using the Android platform. The application selects the best 3 beacons` signals and performs the geo-localization technique for estimating the location coordinates. Using this approach, 1,021 location points are recorded in a day with the sampling interval of 5 seconds, and later stored in the document database (MongoDB) for further processing. Later, R studio is used for executing the preprocessing task i.e. data cleaning. For transforming processed trajectories into semantic trajectories, we have used our data model STriDE (Spatio-temporal Trajectories in Dynamic Environment) [19] (see Fig. 1 showing the logical connections between different STriDE model entities, timeslices, concepts, and user profiles).

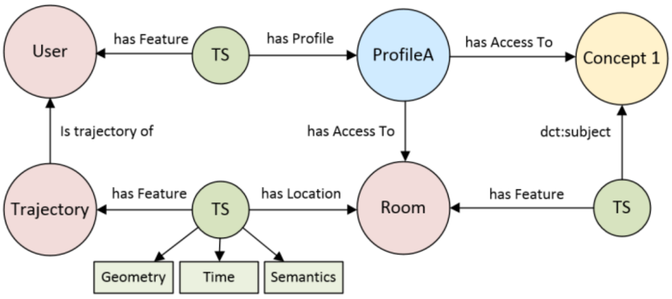

Fig. 1. The STriDE model (user, trajectory and room are the entities that may change over time. Whereas, TS is the timeslice and concepts are defined using SKOS. Each entity is represented using a TS having the start and end dates).

In Fig. 1, an entity denotes real-world entities consist of an identity, spatial and alphanumeric descriptive properties. The STriDE model is built for the moving objects which change their geometry and semantic information over the evolution of time. In this model, the objects are defined as the class 'feature`s instances. Here, the class 'feature' refers to an identity of an object that distinguishes it from the other objects. To capture the behaviors of moving and changing objects, their movements are represented as a set of trajectories` timeslices. A timeslice consists of an identity, alphanumeric properties, a time component indicating the validity of the timeslice, and a geographical component depicting the spatial representation of the entity [19]. Each timeslice is valid for a certain time duration. In case of any change in the timeslice`s components, excluding the identity, a new time slice is generated inheriting the components of the last known state of the entity [19]. In addition, the STriDE model uses ontologies offering the conceptualization of a specific domain for showing relationships among different 'concepts' as a hierarchy for representing trajectories [19]. Here, a 'concept' is defined as an object with a set of attributes (see Fig. 2, in which a concept defines a building space). In our case, the users, the construction machinery and the workspaces of the building are referred to as dynamic entities which change their properties over time without changing their identity.

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. 2. Users and profiles of workers.

To perform the semantic enrichment using the information extracted from semantic data sources (application domain knowledge and geographic databases), the STriDE model uses an OpenStreetMap (OSM) file of the building and a taxonomy along with a set of semantic rules written in the Resource Description Framework (RDF) language. The purpose of an OSM file is to describe the entire building structure in a data model. To label each key-value pair defined in an OSM file, a taxonomy is created as a hierarchy of concepts written as RDF triples using Simple Knowledge Organization System (SKOS) vocabulary. Using the constructed taxonomy, OSM`s key-value pairs are clustered and maintained using the domain knowledge. In addition, a JavaScript Object Notation (JSON) file is created describing a set of semantic rules to link each OSM object with the taxonomy. Eventually, Java objects are created using an OSM file, semantic rules, and a taxonomy as per the semantic definition. These Java objects are later stored in a Stardog (www.stardog.com), a triple store for achieving the complete representation of the building environment.

4.2 Detecting and Visualizing Intrusions

After transforming raw spatio-temporal trajectories using stored contextual information in the STriDE model into semantic trajectories, user profiling is achieved using ‘concepts’ for detecting intrusions in a building. In the STriDE model, as already described above that we have defined ‘concepts’ for tagging different locations of a building. These concepts are defined using SKOS vocabulary and stored in the ‘concept scheme’. Using the ‘concepts’, all the building locations are described in a model. Because the ‘concept’ of a room or any building location may change over time, it cannot be tagged directly but with its timeslice. By means of ‘concepts’, user profiles are created as shown in Fig. 2. Here, a ‘profile’ is a collection of ‘concepts’ that shows the building locations to which a user holds an access. For creating a user in the model, a profile needs to be specified. This approach will allow us in detecting any user intrusion according to the allocation of the ‘concepts’ to different user profiles. This can be verified by checking each timeslice of the user`s trajectory for the ‘concepts’ that it has access to. So, if the user`s profile allows him to access the room means that the specific ‘concept’ is tagged with its profile then everything is good, otherwise we have detected an intrusion (see Fig. 3).

SPARQL Results (returned in 154 ms)

userName	froom	roomLabel	sdate	edate
User 1	stride:W1002	Storage room	2018-01-02T09:36:00	9999-12-31T23:59:59

Fig. 3. Detecting an intrusion from trajectory`s timeslices

For our study, Autodesk Revit (a BIM software) is used because of its open-sourced Application Programming Interface (API) support and extensive use in the construction industry [20]. The building which is used for the experimentation, its BIM model doesn`t exists. For showing a proof-of-concept integration of systems, a sample Revit model file is used. To take advantages from the functionalities offered by the Revit API, a visual scripting tool Dynamo is used as a Revit plug-in [20]. Dynamo graph constructed for the STriDE-BIM integration consists of four main steps which are; a) All the building locations (tagged as 'rooms') in the BIM model are extracted by defining a category of elements as 'rooms' in the Dynamo. b) After extracting a list of room names, 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. c) 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 on a BIM model using the mapping of room names in both lists (see Fig. 4). d) As soon as the problematic room is highlighted on a BIM model, 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.

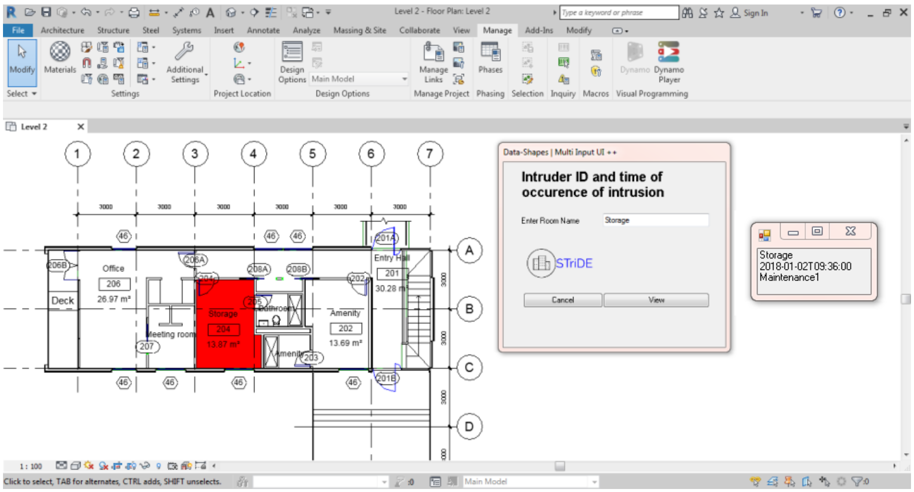

Fig. 4. Visualizing STriDE data in Autodesk Revit software.

DISCUSSION AND CONCLUSION

The proposed system captures raw spatio-temporal data from low energy Bluetooth beacons, and constructs semantic trajectories using the STriDE model. The main feature that distinguishes our STriDE model from the previous trajectory models is that it holds an ability of tracking the relevant semantic information related to the change in geometry and functionality of the building spaces for modeling the semantic trajectories of moving objects (workers and machinery) on a construction site. Another important feature that differentiates our developed system from the existing systems is that, we have integrated the output of our semantic trajectory data model with a smart city solution i.e. open-sourced BIM platform for the industrial users. The reason of using BIM is that, it`s a preferred approach for generating a building visualization in the Architectural, Engineering and Construction (AEC) industry [21]. It aims to provide reliable and up-to-date information about a facility throughout the building lifecycle to AEC team members for conducting studies, simulations and operations [21]. In addition, application of BIM enhances the inter-organizational collaboration of information among members because it is based on the Industry Foundation Classes (IFC) standard that is universal and supports easy and fast information exchanges [21].

The system is developed using semantic trajectories and BIM will help building supervisors and Health and Safety (H&S) managers in achieving the access control of workers to hazardous locations in building or on construction sites. In case of detection of an intrusion, an intruder can be recognized easily from its trajectory identification using a BIM software, and necessary actions can be performed to avoid unsafe situations. As this proposed system is still in the development phase and further work is required to test a developed system on a real construction site and to evaluate it based on its tagging accuracy of the semantic locations with the corresponding spatio-temporal trajectory points. Though, using the designed system on a construction work site will not compromise its usefulness but will raise concerns in the process of location data acquisition. Placing beacons on the building infrastructure and making sure that beacons remain intact to their original positions during dynamic nature of construction works can be challenging. However, the use of advanced geo-localization technologies can be considered for increasing the accuracy of the acquired spatio-temporal data to study worker behaviors for safety management.

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