Exploiting Semantic Trajectories using HMMs and BIM for Worker Safety in Dynamic Environments

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***Abstract*— Understanding dynamic behaviors of moving objects using positioning technologies for construction safety monitoring is still an open research issue. One task; that is a small subset in the widespread field of objects dynamics is the enrichment of the location data of users with the semantic information for studying their mobility patterns in the context of the environment. However, incorporating the semantics related to the environment gets complex in case of the dynamic construction sites where the site spaces are kept evolving with time. For instance, new walls and infrastructure supports are added often on sites, while others are detached. Similar situations open more challenges to keep track of the changes in the attributes of the locations which involve with time for integrating semantics into the location data. Eventually, such changes to the site` locations will result in different user mobility patterns. For capturing the semantics of a dynamic environment and then understanding the user mobility patterns, a system is proposed based on semantic trajectories and Hidden Markov Model (HMM). In the end, Building Information Modeling (BIM) approach is used for visualizing the categorized user movements to help safety managers in monitoring site activities remotely by preventing other workforce from accessing such hazardous locations that involve unsafe movements.**

Keywords—Semantic trajectories; Building Information Modeling (BIM), mobility; Health and Safety (H&S); Hidden Markov Model (HMM)

I. Introduction

The construction industry is one of the largest industries and a major contributor to the economy [1]. Unfortunately, this industry is known for the least safe sector as compared to the other work sectors because construction workers are frequently exposed to the harsh environments [2]. Such uncertain and dynamic working environments consequence in high occurrences of serious injuries and even deaths [3, 4]. According to the Bureau of Labor Statistics (BLS), in 2016 out of 5,190 fatal occupational injuries, 937 were recorded from the U.S. construction industry [5]. Regardless of numerous efforts and more attention being paid to safety management practices in recent years [7], the rate of accidents in the construction industry continues to be high.

The above statistics show that existing site monitoring systems for worker safety are not adequate for reducing fatal accidents. A closer look to the recent research reveals that one of the main reasons for construction accidents is because of unsafe worker mobility behaviors resulting in serious collisions with site objects and machinery [5]. For example, limited spatial awareness of the operating equipment involving sharp movements and rotations within the workers` proximity due to blind spots and surrounding noise can lead to hazardous situations on sites [8]. The latest technological developments in the location tracking systems have made very convenient to monitor sites for detecting unsafe worker behaviors [9]. The spatio-temporal points collected from a typical location acquisition system contains location coordinates with timestamps [10]. These raw points are transformed into finite meaningful episodes called trajectories after performing pre-processing techniques [10]. To achieve semantically enriched trajectories for enabling the desired understandings of the movements specific to the application, related contextual data of the environment needs to be integrated with the trajectories [11]. There exist many approaches in the literature for the semantic enrichment of trajectories [10-13]. The majority of these approaches are primarily designed for outdoor trajectory application scenarios and don't have the capability for tracking the evolution of the building environment for constructing semantic trajectories. In order to perform semantic enrichment of trajectories by keeping track the dynamic building environment where the building objects are moving and changing with time, we have used our STriDE (Semantic Trajectories in Dynamic Environments) model. The main research objective of this study is not only to construct semantic trajectories but also to recognize the unsafe worker movements that can lead to accidents. As for recognizing and categorizing the movements, many case studies are present in the literature based on machine learning algorithms [14, 15]. Among them, statistical HMMs along with the Viterbi algorithm have been applied widely in many works and proved to be the most appropriate choice for categorizing movements and extracting patterns [16]. After using the HMMs, the categorized user movements are visualized using the Building Information Modelling (BIM) approach. The basic idea of using BIM is to have an interactive smart building model [17] that contains building geometry and real-time information related to the building locations which are more susceptible to have unsafe movements of the users. BIM-based visualizations can be used by the H&S managers that can lead to improved safety management intervention strategies by visualizing high-risk workers movements on a building map in real-time for preventing accidents.

The paper is organized as follows. Section 2 introduces the related background literature. Section 3 presents the proposed solution for categorizing worker movements using HMMs and visualizing them on BIM. Section 4 discusses the proposed system, its benefits, and a conclusion.

II. BACKGROUND

The existing literature was initially reviewed to systematically collect information for identifying and understanding the problem domain, which is to identify unsafe movements of construction workers from their semantically enriched trajectories. Nevertheless, trajectory pre-processing is the first step towards constructing semantic trajectories [10]. The basic idea of pre-processing the trajectories is to reduce the data processing overheads without compromising the precision of the trajectory data [10]. The fundamental tasks of pre-processing include noise filtering (removing location points resulted from the weak signals of location systems), trajectory reduction (reducing trajectory size to minimize computation overhead), and stay points` detection (identifying stay regions within a specified distance) [10, 11].

After pre-processing the trajectories, a data model is required for storing the trajectories for the desired analysis. In the literature [18], there exist four types of trajectory data modeling approaches which are; data type-based modeling, design pattern-based modeling, ontology-based modeling and hybrid-based modeling. The data type-based models combine spatial, temporal and thematic dimensions to represent the trajectories. However, the main limitations of data type-based models are the dependency of the trajectory data types on the applications and imposing the use of a generic data type for representing trajectories for all the applications. To address this drawback, Parent et al. designed pattern-based model [19], that is based on Model Analysis and Decision Support (MADS) for supporting spatial and temporal objects and their relationships using spatial extent and lifespan of the trajectory. It represents trajectories as a series of 'stop' and 'move' segments having 'begin' and 'end' timestamps. However, for defining such trajectory segments, the contextual information needs to be fed to the model as per the application requirements. Ontology-based models offer a multi-layered structure for representing the trajectories using the concepts and objects described in ontologies [20] (for example; Yan and Spaccapietra [11] and Noël et al. [21]). If ontology-based models are compared with formally discussed two models, the ontology-based models represents richer semantic information by integrating different types of information enrichment processes [18]. Existing literature also presents solutions based on hybrid modeling approaches for combining the best features of different models for constructing trajectories [18]. An example of such model is discussed by Yan et al. [11] offering three different levels of data abstraction (raw trajectories, trajectory episodes in 'stop' and 'move' segments and semantically enriched trajectories) by encapsulating geometry and semantics of trajectories together.

After reviewing the existing literature on semantic trajectory data models, it is concluded that the existing trajectory models are majorly designed for dealing with the outdoor user trajectories. These models are not capable of tracking the semantic information generated due to the change in the attributes (spatial, temporal and alphanumeric properties) of the building objects for generating semantic trajectories for indoor trajectory application scenarios. For our case, tracking users in the dynamic environment which consists of an indoor as well as outdoor environment settings that can be best studied on the construction sites, where the new walls and infrastructure supports are often added, while others are detached. This opens more challenges to keep track of the changes in the attributes of the locations which involve with time for representing semantic trajectories [20]. For example, a storage zone in the building is now a work zone having a different functionality. Another example would be, due to the placement of the hazardous construction material, the dumping zone on a site became a restricted zone. Moreover, the dimensions of the dumping zone are changed because of the construction of a new wall on a site. Alike situations occur very often on the construction sites. Such changes in the purpose or the position of the locations in the buildings or on construction sites will result in different movement patterns of the users. The updated semantic information about the locations along with the previous information is required to capture for studying the movement behaviors of the building objects including the users in detail with respect to the changes occurred in the building environment. In order to address the requirements (as discussed above) of the dynamic building environments which involve moving and changing objects, we have used our STriDE model that is based on ontologies [20]. The STriDE model is derived from the Continuum model [22] and has the ability to store data of dynamic objects. To track changes in shape, size and attributes of dynamic objects (a user, a trajectory and a room), the STriDE model uses the concept of timeslices as shown in Fig. 1.

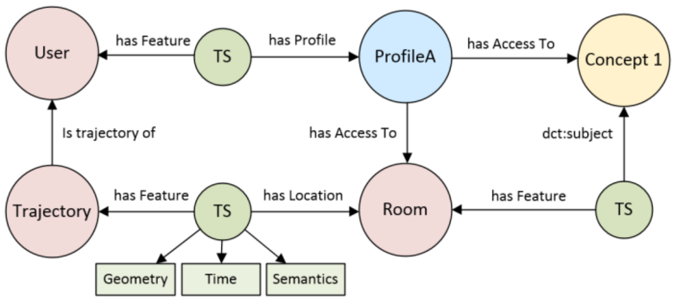

Fig. 1. STriDE data model representing dynamic entities (a user, a trajectory and a room) each with a timeslice (TS) and concepts are used for user profiling

A timeslice consists of four components: an identity, properties having alphanumeric values (semantic component), a time component indicating the validity of the timeslice and a spatial component depicting the geographical representation of the entity. In case of any change in the components of the timeslice, excluding the identity, a new timeslice is created inheriting the components of the last known state of the entity and then those changes are applied. This newly created timeslice is then linked with the previous one to keep the evolution of the entity during its lifecycle. The STriDE model involves mapping trajectory episodes to the meaningful information such as; the mapping of places of interest that can be in the form of Points of Interest (POIs) and the Regions of Interest (ROIs). This is achieved by annotating a trajectory with a meaningful geographic region that requires computation of topological correlations [23]. These correlations are made with third party data sources containing spatial regions having the semantic places [23]. For this, spatial data from an OpenStreetMap (OSM) file is extracted and stored in the STriDE model to make spatial joins i.e. $Trajectory\_epidode \bowtie_{\theta} Region$ for achieving annotations. After the semantic enrichment process, we have categorized the worker movements using the HMMs.

Existing literature shows a straightforward solution for describing the object behavior in time is the Markov chain (MC) model [24]. HMMs are the direct generalization of MCs which assumes that we cannot directly observe the exact states of the system and only a stochastic function of these states is visible to us [25]. HMMs are used extensively in real-world applications for studying the behavior patterns of moving objects. Numerous studies have been conducted based on the smart cameras, wearable sensors, and GPS devices to collect location data to track people, and other moving objects to investigate their different movement behaviors for better decision making. Understanding the building occupancy patterns, abnormal behavior identification and detection of dangerous activities of people, behavioral surveillance system for elderly care-and safety risk assessment on construction sites are the major HMM applications using the location data [24-26]. In all the applications discussed above, there have been three fundamental scenarios [25] for which HMMs are used. These scenarios are the following; 1) Computing the probability of the observation sequences using the given HMMs. 2) Extracting the most optimal hidden state sequences which best explains the observations using the given HMMs. 3) Adjusting the values of the state transition probabilities and the output emission probabilities of the HMMs for maximizing the probabilities of the observation sequences. However, this work focuses on the latter two scenarios.

III. SEMANTIC TRAJECTORY ANALYSIS SYSTEM

Worker movements are highly uncertain on construction sites as their activities are likely to deviate from a predefined planning due to the dynamic environments [8, 9]. These uncertain worker movements have a tendency to creating safety risks that can result in hazardous situations [7]. The most effective way of preventing such situations is to monitor the buildings and the construction sites in real-time to identify unsafe movements of the workers [9]. Existing literature [27] shows that the movements of moving objects can be monitored if step lengths and turning angles are periodically calculated from their trajectories. However, before extracting different users` movements, we need to identify specific regions in a building or on a construction site where the users are staying for a longer duration. These stay locations [10] which are termed as 'semantic regions' in our study are more critical to be monitored than moving locations as the workers are spending most of their time there. To achieve this, a prototype system is developed as a proof of concept application. In the prototype system, spatio-temporal points of the users are collected using 200 Bluetooth beacons placed on different locations in a building. Then, pre-processing tasks are performed on the spatio-temporal trajectories and stay regions of the users are identified inside the building using Zheng et al. approach [10]. Each stay region contains a set of trajectory segments of the users. These trajectory segments are semantically enriched in terms of their corresponding Points of Interest (POIs) locations` information using the STriDE model.

For the semantic enrichment process, STriDE model requires an OSM file for a building under analysis, a set of semantic rules and a taxonomy. The OSM provides spatially rich geographic vector data in an XML format that is open and well-documented having the authorization for utilizing, copying or editing it [28]. OSM data model contains nodes, ways and relations. In addition, an OSM entity can be tagged with single or multiple key-value pairs to add information. This information can be as simple (e.g. label) or complex (derived information from safety instructions) as per the application`s requirements. These key-value pairs are clustered and maintained with the help of taxonomies created by the domain experts. In our case, an OSM file is used in which boundaries of the areas of the building regions are defined along with their links to each other. The file carries the complete building plan and its surroundings for defining the building structure.

For labeling, each building location, a taxonomy is created in accordance with the building requirements. The created taxonomy is a hierarchy of concepts written as RDF triples using SKOS (Simple Knowledge Organization System) vocabulary. In addition, semantic rules are constructed in the form of a JSON file for linking each OSM object with the taxonomy. Then, OSM file along with semantic rules are fed to a 2-step Java parser. Firstly, the parser will establish the mapping between each OSM entity with the Java object. Secondly, using the semantic rules, these constructed objects are transformed into new Java objects according to the semantic definition. These processed objects are later stored in a Stardog (www.stardog.com), a triplestore for achieving the complete representation of the building environment. In the STriDE, a geometry of an object is defined outside the main entity during the data modeling. Here, an entity is describing the identity of the building location. For our scenario, on construction sites, the geometry of locations is changing over time. In order to log changes in shape, size and attributes of dynamic entities, we have used the concept of timeslices. Using this stored semantic data from a triple store and multifaceted characteristics extracted during the pre-processing of trajectories, semantic trajectories are generated as shown in Fig. 2 and 3. After achieving the semantic trajectories, a set of trajectories belonging to a semantic region are further analyzed to categorize users` movements using the HMMs along with the Viterbi algorithm [24].

A. Categorizing user movements using HHMs

An independent HMM is initially trained for categorizing the worker trajectory into different movement states for each stay region. According to the existing literature [27], the movement behavior of a moving object can easily be defined by calculating the individual step length and the turning angle. For our case, we

SPARQL Results (returned in 55 ms)

traj	userName	location
stride:TrajOfMaintenance1-1	Maintenance 1	Outdoor pathway
stride:TrajOfMaintenance1-2	Maintenance 1	Storage room
stride:TrajOfUser1-1	User 1	Outdoor pathway
stride:TrajOfUser1-2	User 1	Corridor of floor 0
stride:TrajOfUser1-3	User 1	Office 1
stride:TrajOfUser1-4	User 1	Corridor of floor 0
stride:TrajOfUser1-5	User 1	Outdoor pathway
stride:TrajOfUser1-6	User 1	Storage room

Fig. 2. Semantic trajectories of two users

SPARQL Results (returned in 47 ms)

s	p	o
stride:TrajOfUser1-1	rdf:type	stride:TimeSlice
stride:TrajOfUser1-1	stride:hasStartDate	2018-01-02T09:00:00
stride:TrajOfUser1-1	stride:hasFeature	stride:TrajOfUser1
stride:TrajOfUser1-1	stride:hasEndDate	2018-01-02T09:05:00
stride:TrajOfUser1-1	stride:isTrajectoryOf	stride:User1
stride:TrajOfUser1-1	stride:hasLocation	stride:W1

Fig. 3. Timeslices of a trajectory; each consisting of an identity for its representation, valid period of time and a geometric component for the spatial representation

have used values of 'step length' (distance between two trajectory points) and 'turning angle' (change in direction in radians from the previous point to the current point), which were extracted during the pre-processing of trajectories. Step length (l_t) is calculated using the Haversine distance formula [27] between the locations (x_t, y_t) and (x_{t+1}, y_{t+1}). The reason for using the Haversine distance formula is because it is one of the preferred methods for calculating the geographic distance between two points on a sphere [11]. While the turning angle is calculated as the change in the bearing between two time intervals. For training the HMMs, four hidden states are defined using different values of 'step length' and 'turning angle' as shown in Table 1. The reason for choosing such number of states is based on the Akaike Information Criteria (AIC) [29]. The purpose of defining such hidden states is to identify unsafe worker movements having walking speed exceeding from 1.4 meter/second (greater than 84 steps/minute) and sharp rotations within the stay region. For defining the hidden states, we have used Gamma distribution for step lengths and Von Mises distribution (also known as the circular normal distribution) for turning angles. After defining the hidden states, we have used Baum-Welch algorithm [25] in the R studio that allows learning parameters of the HMMs. However, before training the model, we need to input initial probabilities. For our case, there are four different states which are 'short steps and fewer turnings', 'short steps and many turnings', 'long steps and fewer turnings', and 'long steps and many turnings' are denoted as S_1, S_2, S_3 and S_4. Dividing the total probability equally for all the states. This will give us initially estimated states` probabilities as; $\pi = \pi_1, \pi_2, \pi_3, \pi_4 = [1/4 \quad 1/4 \quad 1/4 \quad 1/4]$

In order to fulfil the requirements of real construction processes, initial probabilities should be calculated based on the existing situation of the construction sites, and using historical records for improved accuracy in prediction methods. After computing the transition probabilities of workers to move between different states using the Baum-Welch algorithm, the most probably occurring values of the hidden states are also extracted based on the output of learned parameters. For this, we have used Viterbi algorithm [25], a form of dynamic programming to extract the most probable sequence of states for a given trajectory.

TABLE 1 CRITERIA FOR DEFINING HIDDEN STATES

States	**Step length (No. of steps in a minute)**	**Turning angle (Radian)**
S_1 Short steps and fewer turnings	steps ≤ 84	angle ≤ π/2
S_2 Short steps and many turnings	steps ≤ 84	π/2 < angle ≤ π
S_3 Long steps and fewer turnings	steps > 84	angle ≤ π/2
S_4 Long steps with many turnings	steps > 84	π/2 < angle ≤ π

B. *Visualizing user movements on a BIM model*

BIM is a term used for describing building activities in an object-oriented Computer Aided Design (CAD) for representing building elements in terms of their geometrical, functional attributes and relationships [17]. While the BIM technology holds building information and n-dimensional visualizations [17], it lacks the real-time data related to the building environment. To overcome this limitation and to make BIM models dynamic for displaying accurate data from deployed building IPS sensors, plug-ins are developed using Application Programming Interface (API) for adding more functionalities in the BIM model for stimulating the concept of smart buildings [30]. For our study, Autodesk Revit (a BIM software) is used because of its open-sourced API support and extensive use in the industry [31]. To take benefits from the functionalities offered by the Revit API, a visual scripting tool Dynamo is used as a Revit plug-in. Dynamo functions alongside the Revit, requiring an active Revit document containing the BIM model and follows a simple execution structure that is; input, process, and output [30].

For displaying the most probable occurring movements that are resulted from the Viterbi algorithm using the context of building locations, a Revit Architecture software along with a Dynamo (a Revit Plug-in) is used. The building that is used for the study, its BIM model doesn't exist. A simple building structure without architectural aesthetics is created in the Revit software by utilizing the information from an OSM file of a building for demonstrating a proof of concept integration of systems. After constructing a BIM model of a building, Dynamo is used for generating the visualizations. Dynamo graph [30] constructed for the our study consists of the following key steps, which are; All the building locations which are tagged as 'rooms' in the Revit 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 the semantic information in the form of 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 identification for each space representing a POI for visualizing the problematic locations in the Revit model using the output of the Viterbi algorithm. The naming convention of Revit rooms is set according to the tagging of semantic points as described in the STriDE model. For visualizing the users` movements on a BIM model, the input trajectory streams of the Viterbi algorithm are semantically enriched with their corresponding POIs` information which is stored in the STriDE model. This information of the POIs is further mapped with the Revit`s room list extracted from an active Revit document for displaying the output of the Viterbi algorithm (the probabilities) using the different colors for representing each movement state of a user. The changes in the color of the Revit rooms are achieved 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 as shown in Fig. 4.

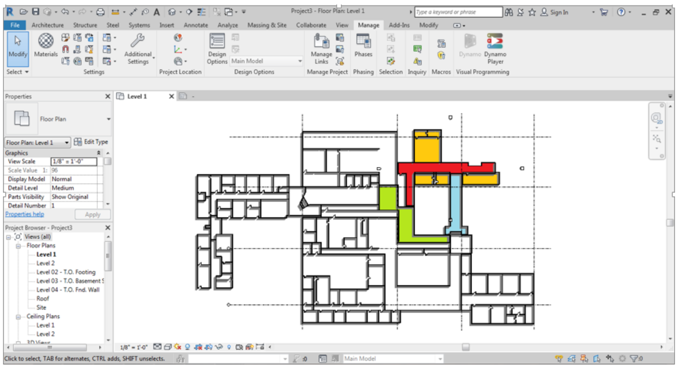

Fig. 4 BIM model constructed for plotting output of the Viterbi algorithm based on the most probable observed states` values as; 'short steps and fewer turnings' in Green, 'short steps and many turnings' in Blue, 'long steps and fewer turnings' in Orange, and 'long steps and many turnings' in Red color.

IV. Discussion and Conclusion

The study explained the functionality of the developed prototype system that uses an IPS technology and HMM-based probabilistic framework for visualizing categorized worker movements within the stay region using the BIM approach. The location data of building users in a day is collected and their stay regions are identified with their stay duration (greater than 20 minutes in our case) in that particular day. The reason for extracting such locations in a trajectory is to identify the semantic regions (ROIs) and their associated POIs. The ROIs are the wider areas of the building (e.g. work-zone237, etc.) as shown in Fig. 5, which consist of multiple geographical POIs (e.g. outdoor pathway, storage room, office1, etc.) labelled as 'rooms' in our model. The idea of dividing a building into different semantic regions is taken from the Pradhananga and Teizer, 2013 research [32]. The developed system has identified a number of stay locations in users` trajectories which relate to different semantic regions. For mapping the trajectories with their corresponding semantic regions, spatial joins are performed as discussed in the section III. Figuring out the amount of time spent by the users in each identified semantic region will give a good understanding to know the rate of utilization of the location. In the similar way, on the sites, trajectories of machinery can be tracked using the semantic regions which covers wider geographical areas for analyzing how often machinery enter a particular site location and for how long it stays over there. This information will help building supervisors and H&S managers in managing the building or site resources effectively in real-time by knowing the locations and machinery` usage.

user	location	concept	start	end	duration
Maintenance 1	Storage-zone-300	stride:Storage	2018-01-02T09:05:00	2018-01-02T12:00:00	175
User 1	Work-zone-237	stride:SafeWorkzone	2018-01-02T09:06:00	2018-01-02T09:59:00	53
User 1	Work-zone-237	stride:DangerousWorkzone	2018-01-02T10:01:00	2018-01-02T11:15:00	74
User 1	Storage-zone-300	stride:Storage	2018-01-02T11:21:00	2018-01-02T12:00:00	39

Fig. 5. Semantic regions of a user with start and end timestamps, and duration in minutes

For further semantic annotations, a semantic region is taken into consideration and trajectories belonging to two users (User1 and Maintenence1) (see Fig. 2) are broken down into multiple timeslices using the STriDE model. The process of constructing multiple timeslices is achieved based on the detection of a change in the components (spatial, temporal and semantics) of a user trajectory`s timeslice as shown in Fig. 3. After extracting the semantic stay regions, an entire set of trajectory points belonging to a particular stay region is further analyzed using an HMM along with a Viterbi algorithm for identifying unsafe user movements involving long steps and many turnings per minute within different POIs. The purpose here is to understand the movements within the trajectories with respect to identified POIs corresponding to different building regions. There are unsafe movements identified by the Viterbi algorithm having long steps or many turnings as the 4th state that is visualized using the BIM model (see Fig. 4). The reason for using a BIM approach is because, it is becoming a worldwide standard in the Architecture, Engineering & Construction (AEC) industry [31]. Our system functionality of analyzing semantic trajectories that is integrated with a BIM works as a plug-in that aims to enhance the present capabilities of a BIM software by providing a reliable and up-to-date information about the different types of users` movements occurring within the facility throughout the building lifecycle to AEC team members for conducting further studies, simulations or operations using building occupants` mobility data.

Visualizing the results of HMMs using the BIM after analyzing the semantic trajectories will enable the system users (H&S managers and building supervisors) to see the exact locations where the unsafe movements are occurring in real-time during construction and facility management operations. In addition, the system will also help building supervisors in maintaining safe distances between the workers and the construction machinery operating at high speed or many turnings, and this is achieved by increasing the level of spatial awareness [33] about sites using semantic trajectories. Such real-time visualizations can result in preventing the occurrence of accidents because of an excessive proximity between the workers and the machinery. Moreover, if the construction equipment is not being operated in the safe speed limits on a construction site [32], such visualizations of unsafe movements using a BIM model will help H&S managers in identifying the workers who are not complying the safety regulations and the requirement for machinery operators` training will be determined accordingly. Furthermore, understanding different movements of the workers and the machinery [32, 33] will act as a pro-active measure for preventing fatalities and the planning of the future construction operations can be readjusted by the building supervisors to avoid unsafe situations.

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