DNAS-STriDE Framework for Human Behavior Modeling in Dynamic Environments

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Abstract. Numerous studies have been conducted over the past few decades on human behavior modeling and simulation by incorporating the dynamic behaviors of people for different Facility Management (FM) applications. For example; the Drivers, Needs, Actions and Systems (DNAS) framework which provides a standardized way to conceptually represent energy-related occupant behaviors in buildings and allows the exchange of occupant behavior information and integration with building simulation tools. Despite numerous studies dealing with dynamic interactions of the building occupants, there is still a gap exists in the knowledge modeling of occupant behaviors for dynamic building environments. Such environments are best observed on construction sites where the contextual information linked to the building spaces evolve often over time in terms of their location, size, properties and relationships with the site environment. The evolving contextual information of a building is required to be mapped with the occupant interactions for an improved understanding of their changing behaviors. To fill this research gap, a framework is designed for providing a 'blueprint map' to integrate DNAS framework with our Semantic Trajectories in Dynamic Environments (STriDE) data model to incorporate the dynamicity of building environments. The proposed framework extends the usability of a DNAS framework by providing a centralized knowledge base that holds the mobility data of occupants with relevant historicized contextual information of the building environment to study occupant behaviors for different FM applications.

Keywords: Behavior, Knowledge Modeling, Spatio-Temporal, Safety Management

1 Introduction

Humans are the important factor for building FM operations as they impact the building environments actively (i.e. production of heat because of their presence) and passively (i.e. operating building appliances) [1]. For ensuring an appropriate level of

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quality of services to the building occupants, the most crucial challenge faced by the facility managers is to understand the occupant behaviors and their interactions with buildings [1, 2]. Although, this is a complex activity because the occupant behaviors and the buildings are dynamic in nature and context-dependent. Here, a context refers to any information based on the contextual factors such as space, time and environment utilized for categorizing the situation of occupants [3]. Failure in understanding occupant behaviors because of inadequate integration of all relevant contextual factors associated with the occupants and the building environments can result into serious financial and management crises such as under-utilization of the building spaces, decreased productivity due to poor environmental conditions, increased energy usage, and safety hazards [1 - 4]. On the contrary, if the occupant behaviors are modeled and predicted effectively by incorporating all the possible contextual factors (social-personal, economic, etc.) which may influence occupant behaviors will lead to an increased physical comfort, enhanced safety at work and improved work performance of the occupants while keeping the level of building resources to the optimum [1, 5]. Existing literature [4 – 9] encompasses many studies for constructing occupant behavior extraction systems which help facility managers in decision making for FM operations by modeling dynamic behaviors of building occupants which change over time according to the building environment. Despite numerous existing studies which model dynamic interactions of the building occupants, there is still a gap exists in the knowledge modeling of occupant behaviors for dynamic building environments. To fill this research gap, one of the prominent occupant behavior models i.e. DNAS is selected from the existing literature [4] based on its relevance to our case-study and popularity that is perceived from its citations. For incorporating the dynamicity of the building environments in terms geometry and contextual information, a frame-work named 'DNAS-STriDE' is proposed which aims to serve an extension of the original DNAS by integrating the conceptual modeling of DNAS with our data model named 'STriDE' (Semantic Trajectories in Dynamic Environments) [10]. The resulted framework by integration has provided a centralized knowledge base that holds the mobility data of occupants with relevant historicized contextual information of the building environment to study occupant behaviors for different FM application scenarios in buildings.

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.

2 Background

Behaviors are the interactions (leaving or entering a room, visual and thermal indoor conditions adjusting using windows or blinds, doors, etc.) of building occupants which can be categorized into different movements, simple presence or actions with their environment (building, its systems and appliances) which impact on the building performance (heating/cooling, indoor air quality, energy, comfort, etc.) during a

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building lifecycle [1, 2, 4, 5]. In majority of the situations, the occupants` presence is the precondition for any kind of behavior understanding as building occupants can only interact with the building environment if they are present inside the building [1]. Thereby, an occupant interaction which results in changing a building state (presence or absence in case of occupancy monitoring) or no interaction leaving the present state of a building unchanged are both facets of occupant behaviors [1]. For understanding the occupant interactions, the modeling process of their behaviors conventionally initiates from the data acquisition of occupants along with the building environmental and infrastructural parameters [5]. The quality of data captured from various types of sensor data acquisition systems differs greatly in terms of the resolution of the sensors deployed [1, 5]. Spatial, temporal and occupant resolutions are combined for determining the overall resolution of the system for capturing the occupant behaviors. As the resolution of the captured sensor data increases, the building space gets more precise, the occupants become more distinct based on their identities and the information from the sensor data is accessible faster [5]. For example, a low-resolution system will only capture the binary information (presence/absence) of the occupants in a specific time where the identities of the occupants are not recognized. Whereas, a high-resolution system will be able to detect the number of occupants, their identifications, as well as their activities [5].

Once data is acquired of occupant behaviors, the studies are performed on the collected data and correlations are extracted between the occupant behaviors and the building parameters using a set of contextual factors. For modeling the occupant behaviors, conventionally there exists four types of approaches [1, 5] which are: 1) static-deterministic, 2) static-stochastic, 3) dynamic-deterministic and 4) dynamic- stochastic. After applying the most appropriate modeling approach, a process of understanding occupant behaviors is evaluated to find out the reliability and effectiveness of the employed model used for extracting insights. The whole process of modeling occupant behaviors and evaluating a model is iterative which helps in tuning the model for best results [1, 5]. As a result, occupant behavior model functions as a stand-alone system or the output of the model is linked with the Building Performance Simulation (BPS) programs or Building Information Modeling (BIM)-based tools for further experimentations or generating information-enriched visualizations [5].

3 DNAS-STriDE Framework

After an extensive review of behavior modeling, it is observed that majority of the existing systems [4 - 9] model human behaviors by capturing the stochastic and reactive nature of their behaviors in building environments. However, these models do not incorporate the information of complex dynamic environments where the building objects evolve over time. For example, DNAS framework of Hong et al. [4] which is based on ontological modeling and used for describing the impact of occupant behaviors on energy use of buildings. This impact is represented using four components which are; drivers, needs, actions and systems. These four components of the framework encompass the building environment and cognitive processes of the occupants.

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DNAS framework has provided a basic ontological method for representing the energy-related occupant behaviors. However, DNAS requires more developments so that it can be used as a stand-alone or an integrated solution for extracting insights about occupant behaviors in dynamic environments. For this, DNAS-STriDE integrated framework is proposed which offers; 1) a centralized knowledge base for mining behavioral interactions of the occupants which can be in the form of occupant-to-occupant, occupant-to-building or building-to-occupant interactions, 2) a process of data enrichment of DNAS ontology using the results of a state-of-the-art machine learning model (Hidden Markov Model (HMM) in our case) in the form of 'hidden states' which are used to find the correlations and patterns in the acquired sensor data for studying the occupant behaviors, moreover 3) incorporation of the dynamicity of the building locations in data modeling stage in terms of the evolving spatial and contextual information over time.

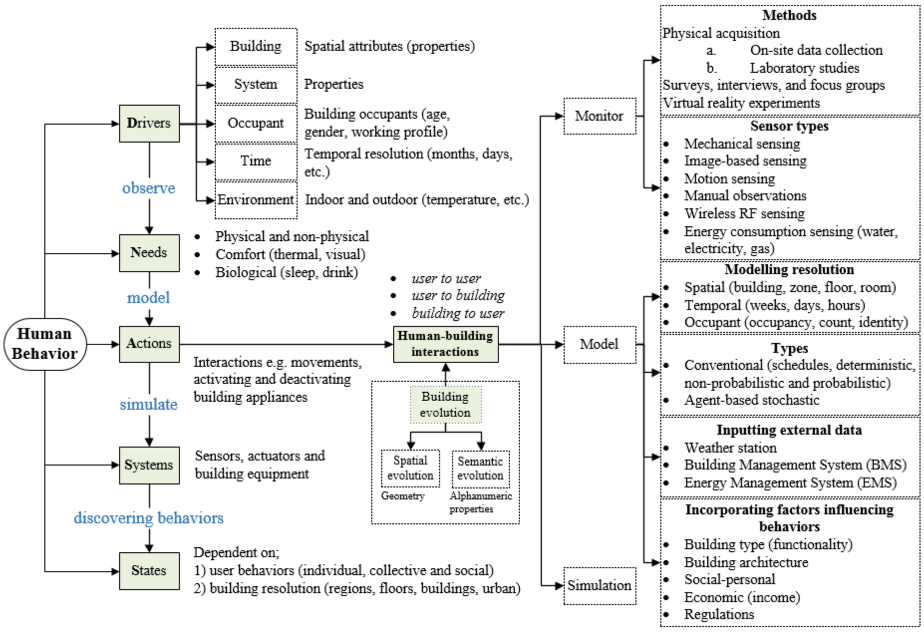

Fig. 1. DNAS-STriDE framework

The proposed framework (see Fig. 1) requires sensory data to perform behavioral analysis. The acquisition of relevant sensor data is based on the application requirement. For example, the safety manager of a building requires to monitor the movements of the occupants in a building. In this case, using our DNAS-STriDE framework, 'driver': monitoring movements of occupants, 'need': safety management in a building by identifying unsafe movements, 'action': tracking movements of occupants using their spatio-temporal trajectories, 'system': Bluetooth Low Energy (BLE) beacons for sensor data acquisition and 'states': 1) static (no movement), 2) normal movement ($0 <$ steps ≤ 84 and $\pi/2 \leq$ angle $< \pi$) and 3) risky/unsafe (steps > 84 angle $\geq \pi$). More information on movement states can be found in [11]. For understanding mobility-based behaviors for a safety management application, BLE beacons are installed on different building locations. After sensor data acquisition, the acquired location data is transformed into trajectories after preprocessing (i.e. filtering). More information on trajectories and their preprocessing can be found in [3]. After preprocessing the trajectories, the STriDE model is used for the semantic enrichment [3, 10] for incorporating the contextual and application-based information in processed trajectories. The STriDE model is based on a Continuum model that can stores data as well as performs semantic enrichments of moving and changing objects` trajectories [10]. For the semantic enrichment, the STriDE model uses a set of classes and properties from the existing vocabularies. The vocabularies are used for defining the concepts and their relationships by classifying the terms. Our STriDE model uses three different vocabularies which are; 1) Simple Knowledge Organization System (SKOS), 2) Dublin Core Terms (DCT) and 3) GeoSPARQL (GEO).

For tracking the evolution of building objects (users, trajectories and rooms), the STriDE model uses the concept of timeslices (TSs) [10]. A TS includes four components which are; an identity, alpha-numeric properties, a geographical and a time component [10]. At the occurrence of a change in any component of a TS excluding the identity, a new TS is generated inheriting the components of the last known TS. To show a proof-of-concept application of our DNAS-STriDE framework to hold the building evolution with the semantically-enriched trajectories to study movement behaviors for safety management, let's suppose we have a building from where the spatio-temporal data is collected (as discussed above) and the purpose of one of the building locations is changed (see Fig. 2). The location 'office' is now a 'storage room'. The STriDE model uses 'concepts' for describing the building locations. In Fig. 2, there is a hierarchy of SKOS concepts. It has a skos:hasTopConcept connects skos:Concept room. Two skos:Concept (office and room) are defined. All these concepts form a hierarchy. In addition, there is a profile named employeeProfile which gives access to all the concepts (locations). As soon as the functionality of a room (i.e. a context) is changed, a new TS is created. For instance, a user Jane is an entity of a TS ts-jane$_0$ and her position is tracked by a trajectory tr-jane. We can observe by a link between tr-jane$_0$ and room1 that Jane is in room1. The entity room1 was initially an office as suggested by the dct:subject link of tr-room1$_0$ towards the concept office. Later, this room is changed as a storage room having the same geometry as of the office represented as ts-room1$_1$.

4 Discussion and conclusion

Once the spatio-temporal data of occupants is collected, processed and semantically-enriched using updated building information that is evolving over time, a process of knowledge modeling takes place. Knowledge modeling captures and models the knowledge into a reusable structure for the sake of historization of information, sharing as well as reapplying it for different applications [12]. Our DNAS-STriDE integrated model provides a knowledge model to study occupant behaviors using a building context with the help of stored semantic trajectories. Later, probabilistic models based on the application requirements are applied for categorizing different types of movements using the stored semantic trajectories. For our application scenario of

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safety management in a building, HMMs are used for categorizing the occupant movements. To categorize movements into three states which are static (stay location), normal and risky, the values of step lengths and turning angles are used for defining the hidden states. In Fig. 2, at a time instance, the most probable stay locations of occupants are shown in Green in color using the universal Architecture, Engineering & Construction (AEC) industry standard i.e. Building Information Model (BIM). Whereas, the most probable building locations at a time instance where there are the normal and risky movements of occupants are shown in Yellow and Red in color. Generated BIM-based visualizations provide insights about building occupants` movements in real-time using a building context. As a result, locations with risky movements can be easily identified, and necessary actions can be taken accordingly by the safety managers. Managing the safety in a building by acquiring spatio-temporal data, transforming them into semantic trajectories and exploring the states of the occupants to represent their movement behaviors using five components which are 'driver', 'need', 'action', 'system' and 'state' is one of the use-cases of the proposed framework. However, the proposed framework which adds a new dimension (i.e. hidden state) to study occupant behaviors in the original DNAS framework can be used in different types of other applications for managing the information of occupants and evolving building environment and infrastructure during a building lifecycle starting from a construction phase to a facility management phase.

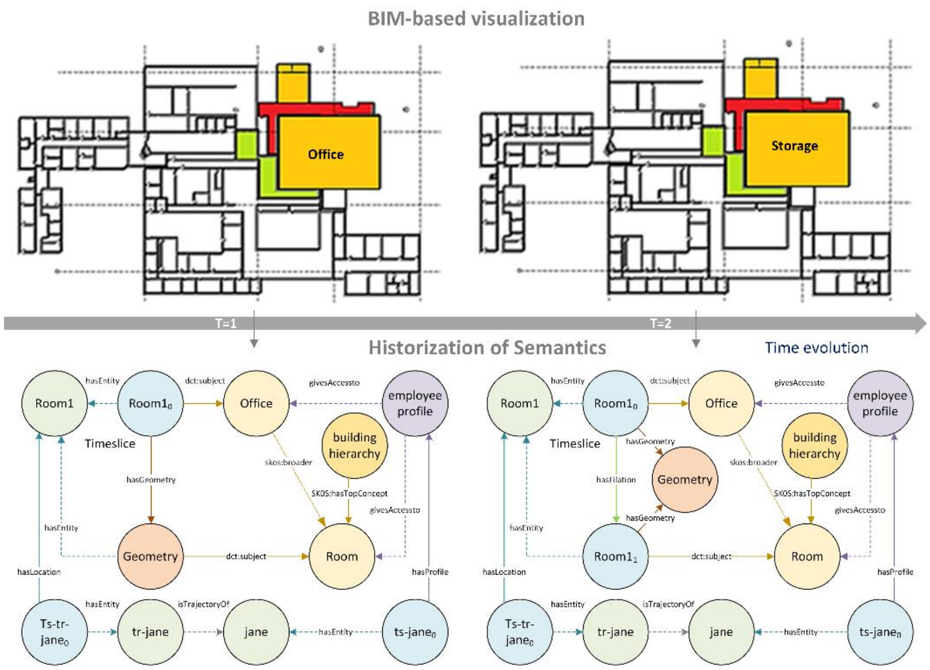

Fig. 2. DNAS-STriDE historization of building evolution (Timeslices are in Blue, entities are in Green, SKOS concepts are in Yellow, profile is in Purple and geometry is in Red color).

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