Utilizing BIM for Real-Time Visualization and Indoor Localization of Resources

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ABSTRACT

Building Information Modeling (BIM) has been found to be one of the most promising advancement in the Architecture, Engineering, Construction, and Operations and Management (AECOM) industry. BIM integrates the geometric and parametric properties of the 3D model of a facility with all the information and properties of building features and components. However, finding the current location of a specific component or navigation through an unfamiliar facility can be difficult and time consuming. Visualizing the location in real-time can provide the ability to reduce the time for manual searching and locating. This paper demonstrates how the BIM model can be utilized for real-time visualization and localization when integrated with sensing technologies. Real-time visualization and localization requires context-aware information (e.g. space, location, time) in order to function properly. Therefore, the BIM model can provide the spatial relationships while the location sensing technology can provide location and time information. Current indoor localization techniques utilize probabilistic algorithms to estimate landmarks or components, which often require great computational power. Since the model contains the exact locations of components, utilizing BIM provides the advantage of not needing to estimate the true location of the landmarks, drastically reducing the complexity and computing time of the algorithm.

PROBLEM DESCRIPTION

In an industry where time is crucial for remaining on schedule and lowering facility management costs, manual inspection remains especially inefficient and costly. Current methods of planning and executing facility management are based on personal knowledge and experience (Akcamete et al. 2010). Additionally, current manual efforts and paper-based quality inspections involve labor-intensive methods and are shown to be unreliable, ineffective, and time consuming (Wang 2008). Additionally, building systems are becoming increasingly complex, causing challenges for the management and operation of the facility (Kean 2011). The process of manual inspection proves to be time consuming as it relies distinctly on a worker searching throughout a facility for problems without precise information relating to location. Manually inspecting or locating these components causes workers to spend excessive amounts of time searching for desired equipment or materials, rather than working efficiently on the tasks required for proper maintenance. It has been shown that locating equipment in facilities is the core maintenance activity that causes significant delay in maintenance (Lee and Akin, 2009). Moreover, locating building components is critical for timely repair of the component and mitigation of the damage (Taneja et al. 2012). Through the use of context-aware (e.g. location, time, three-dimensional space based) automated systems, this process can be greatly improved to increase the performance of facilities management. Real-time access to the locations of workers, materials, and equipment has been a significant advancement to the management of construction processes and facilities management. Location-aware computing offers significant potential of improving such manual processes and supporting important decision making tasks in the field (Khoury and Kamat 2009). There have been a variety of technologies (e.g., Ultra Wideband, Global Positioning System, laser scanner) utilized to produce visualizations of the locations of resources on a construction site. However, there is a lack of real-time visualization of such technologies within an indoor environment to determine a person's location inside the facility, as well as an aid for navigation. The need for such technologies in an indoor setting is crucial since research has shown that 85% of the total project cost is spent in operation and maintenance from the owner's perspective (Teicholz 2004).

One solution is the integration of emerging wireless remote sensing data with Building Information Modeling (BIM) which allows for the real-time visualization of the locations of workers, materials, and equipment (Costin et al. 2012).

BACKGROUND

Building Information Modeling (BIM). BIM integrates the geometric properties of the 3D model of a building with all the building objects and attributes, such as product information, site schedule sequencing, and owner histories (Eastman et al 2008). Integrated building technologies allow a convergence and integration of systems to play a greater role in overall building performance (Kean 2011). The universal circulation network (UCN) presented in Lee (2012) provides a method for representing circulation paths from a BIM model. Utilizing the spatial topology and geometry of the model, the UCN can determine walking distances, including the shortest and most efficient. The ability to calculate circulation paths holds enormous potential for indoor localization and visualization, especially if linked to remote sensing technologies. Making uses of the industry foundation classes (IFCs) (buildingSMART 2013) the model provides two key pieces of spatial information: 1) the coordinates of objects (i.e. IfcCartesianPoint) needed for localization; and 2) the topology and geometry (i.e. IfcSpace) needed to navigate the building.

Context-aware system. Context-aware systems have promising benefits of real-time location of users and utilities for facility maintenance management. Context-aware information includes time, location, and spatial (3D) relationships.

Location sensing technology can provide location and time information and a BIM model can provide the spatial relationships. Circumstances may arise where poor visibility makes detection of utilities difficult for a worker, causing problems to remain unnoticed and resources to remain inoperative. In a situation where the problem is located, additional time is lost while relaying the information to the facility manager for guidance on the necessary corrective measures that must be taken. Moreover, occupants unfamiliar with a facility may have difficultly locating themselves, as well as locating a specific room within a facility. It is also of utmost importance that the facility can be navigated quickly in the event of an emergency, because a search and rescue crew has no time to waste in getting lost when human lives are at stake. A context-aware system can provide occupants, personnel, or emergency crews with location information to navigate around and find their destinations (Li et al. 2011).

Indoor Localization. Indoor localization refers to locating an object or person in an indoor environment by the use of context-aware information. Sensors of different types have been tested and proven in the outdoor construction industry, including GPS and Ultra wideband (UWB). And although both GPS and UWB provide high precision locations, both of these technologies possess several drawbacks for use indoors (Khoury et al. 2009). Indoor localization techniques in the AECOM industry have mainly used Radio Frequency Identification (RFID) and wireless local area network (WLAN) technologies (Pradhan et al. 2009; Taneja et al. 2012; Li et al. 2011).

Simultaneous localization and mapping (SLAM) is a popular technique used for autonomous vehicles to use sensing technology to build a map within an unknown environment (without *a priori* knowledge) while simultaneously using the map to compute its location. There are various forms of SLAM implemented in different environments, but the basic formula and structure are the same. The basic parts of SLAM include landmark extraction, data association, state estimation, state update and landmark update. Durrant-Whyte and Bailey (2006) use the recursive Bayesian formulation for the real-time probabilistic estimation of location at a time instant. Fortunately for the AECOM community, the BIM model can provide the prior knowledge of the environment, drastically reducing the complexity of the SLAM technique.

Received signal strength (RSS) methods determine the location of the tag based on the signal strength received by the antennas. The signal strength propagates and reduces when the distance between the antenna and tag is increased. For instance, the further away a tag is, the lower the RSS. The maximum RSS is the power output from the reader, and the minimum is the signal strength needed to operate the tag. Therefore, knowing the output power from the antenna and the performance characteristics of the antennas and tags, an approximation of the tag location can be made. However, The RSSI values do not correspond to physical positions and can change with various environmental conditions (Fink and Beikirch 2011, Wang 2011). Therefore, additional information is needed to detect the characteristics of the RSS, such as computing RSSI "radio maps" or "probability maps" (Wang 2011). For accurate location detections, every indoor positioning system needs an underlying map for reference (Schafer et al. 2011). Additionally, prior knowledge of the layout of a facility can improve the performance of RFID localization (Taneja et al. 2012).

Current techniques to determine the location of a RFID tag require additional labor-intensive enhancements, such as sensor histogram models, filters, or pre-mapping of tags. The work by Bekkali et al. (2007) introduced a new positioning algorithm using two mobile RFID and a Kalman filtering technique. However, algorithms that require a large number of RSS measure samples to achieve good accuracy can be a limiting factor in processing and storage capacity. Deyle et al. (2008) developed a particle filter works by measuring the forward path loss. Bouet et al. (2008) surveys the current state-of-art of RFID localization techniques and concludes that the choice of technique and RFID technology significantly affects the granularity and accuracy of the location information but also the whole cost and the efficiency of the RFID system.

However, a major setback of localization algorithms is determining the correct room (or space) for the final placement. For instance, if sensors of multiple rooms are read simultaneously, the algorithm may have difficulty putting the user in the correct side room. Fortunately, the spatial information of the BIM model is critical to determine constraints for the final placement.

PURPOSE, SCOPE, AND METHODOLOGY

The purpose of this paper is to demonstrate how the BIM model can be utilized for real-time visualization and localization when integrated with sensing technologies. Taneja et al. (2012) defines an accuracy within 3 meters at 95% precision is needed to guide personnel to the general location of components or equipment in a facility, which then the personnel can distinguish the desired item. Unfortunately, this assumes that the readings are in a single room, and a greater accuracy is needed in order to distinguish from multiple rooms. The scope of this research focuses on the Operation and Maintenance (O&M) phase of the lifecycle of an office building. Passive RFID technology has been selected as the wireless remote sensing technology to be deployed in an indoor environment. In addition to the low cost and high durability, this research takes advantage of the passive RFID tags that are already tagged on building utilities from supply chain management.

A contribution of this research is the real-time display of the localization of a user in a BIM model. Figure 1 is a process flow diagram of the localization and visualization algorithm. The algorithm (Costin et al. 2013) works by first receiving the tag reads from the RFID readers. For each tag read at time k, the (x,y,z) location of that object is retrieved from the database. Using all the tag locations (tag ID) at time k, the algorithm computes the mean location. Supplemental information can be used for adjusting the algorithm, such as the received signal strength indicator (RSSI) and antenna of tag read. For instance, if one antenna reads a tag at high RSSI, the tag has high probability it will be on that side of the cart. Additionally, if that antenna reads a tag with low RSSI, the tag may be further away from the cart or even result from multipath. Finally, the adjusted calculated location is then sent to the BIM model, and the updated location is displayed on the user interface. The readers then read tags at time k+1 and the algorithm repeats.

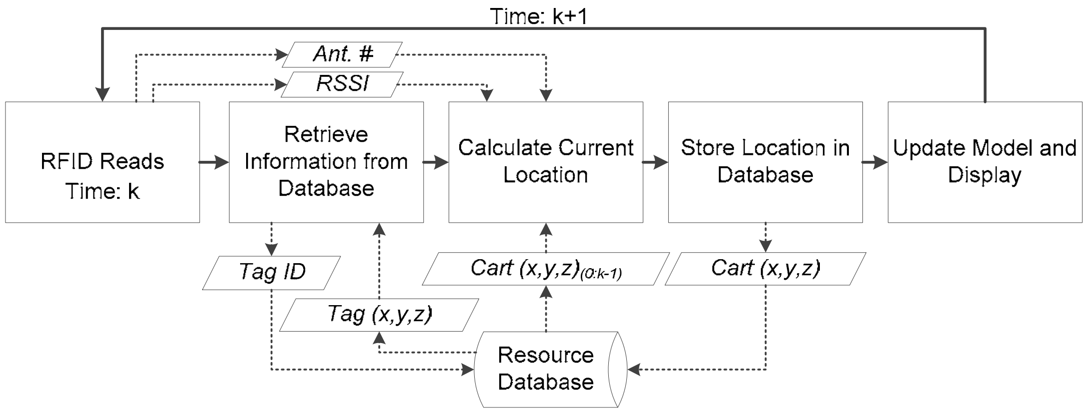

Figure 1. Process flow of localization and visualization algorithm

PRELIMINARY TESTING AND RESULTS

Tekla Structures 19 was selected as the BIM platform and Trimble ThingMagic for the RFID technology. A prototype software application was developed in Visual C# 2010 to connect the ThingMagic API, and Tekla API, with MS Access database. This application links communication between the RFID equipment, BIM model, and resource database. A user interface allows for efficient storage and retrieval of the maintenance data into a database. The object IDs in the BIM model were linked to unique RFID tags and the relation was also stored in the database. Whenever a tag is read, the corresponding object ID in the model was retrieved from the database, along with that objects building information. A prototype mobile cart was assembled to mimic the ones used in facility management. The cart comprises of one ThingMagic M6 UHF RFID reader that connects to four antennas (top, front, and two sides). A wireless router, battery, and laptop computer are also on the cart. The RFID tags selected were Avery Dennison AD-223 860-969 MHz passive tags, which are designed for use in global supply chains.

A straight corridor of the Sustainable Education Building located at the Georgia Institute of Technology in Atlanta, Georgia was modeled in Tekla. The purpose of the following experiment was to calculate the accuracy of the localization and visualization algorithm. Twelve unique tags were modeled at fixed (X, Y, Z) locations, in which six were placed on each wall. Each tag height (Z) was kept at constant 1.10 m, which is the height of the center of the antennas. The height was a control variable because read angles can affect results of the RFID reads. The distance between each tag was also a control variable at 1.50 m. The corresponding tags were deployed at the identical locations in the corridor. The corridor was 2.4 m in width, and a tape measure was secured as the centerline. Starting from point 0.0 m, the cart took a single reading at each 0.5 m mark until the last mark at 7.5 m. The duration of the reading (read rate) was set to 1,000 milliseconds. The experiment was conducted twice trials from 0.0 m to 7.5 m, and them the cart turned around a conducted 2 more times staring from 7.5 m to 0.0 m. There were a total of 64 trials. The data was recorded and passed through the location algorithm. At each trial, the algorithm produces an (x,y,z) coordinate that places the cart in the BIM. The error was calculated from the coordinate produced from the algorithm and the true location at each trial.

Figure 2 demonstrates the visualization of localization in the BIM. The walls and other objects in the model can be set to translucent to help see the cart and tags. As the user pushes the cart, the reader picks up the tags that are in the vicinity. Those tags then highlight in the model and the display is updated. Any of those tags can be selected in the interface to retrieve information about the tagged object. Additionally, the user can select an object from the database (such as when an object needs to be inspected) and that object's location will be highlighted in the model. This feature allows the FM to save much time and effort trying to manually locate the object.

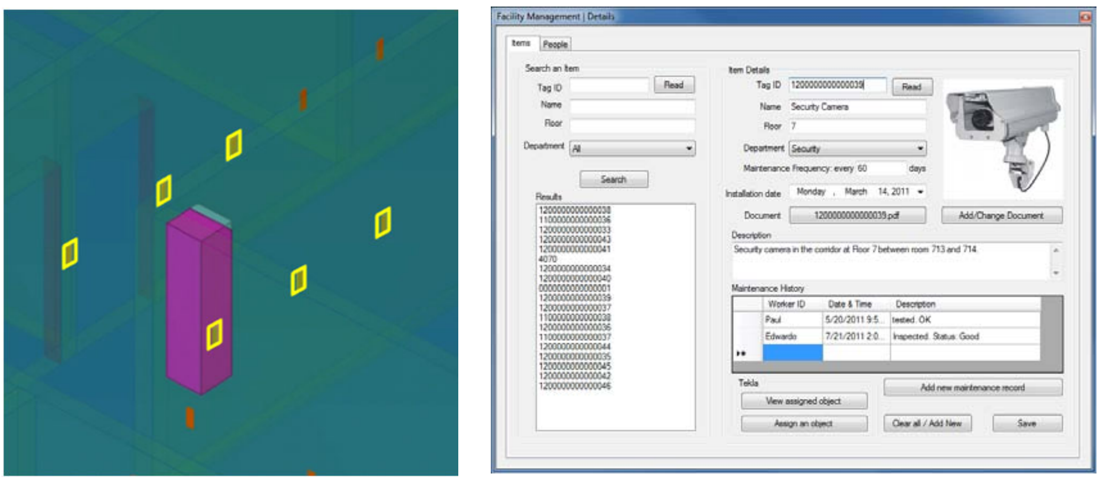

Figure 2. Visualization of localization in a BIM model with highlighted tags (left); and user interface showing details of the selected object (right).

The result of the field tests experiments are shown in Figure 3, a scatter plot showing the error of the estimated locations from the true locations. Error in position is calculated as a distance between the point where the cart is actually located and the location of the cart calculated by the algorithm in both the X and Y directions.

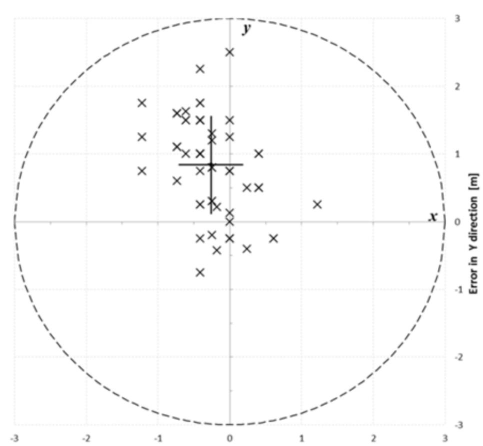

Figure 3. Scatter plot of the localization error.

The goal was to achieve an accuracy of 3 m (outer dashed circle) at 95% precision. Each "x" marks the calculated distance from the true location. The mean error for the Y direction was 0.84 m with a standard deviation of 0.72 m (solid vertical bar). The mean error for the X direction was -0.26 m with a standard deviation of 0.45 m (solid horizontal bar). Using a standard Z-test, the 95% confidence interval for the system error is 0.84 ± 1.41 m, which lies within 3 meter target (for laboratory conditions).

CONCLUSION

Real-time visualization and localization requires context-aware information in order to function properly. The integration of real-time location tracking data in BIM provides the context-aware information for visualization and localization. Although this research used passive RFID with Tekla, the methodology of linking sensing technology with BIM can provide many useful applications to optimize safety, security and productivity in the AECOM industry. Automated maintenance history and maintenance schedule can be generated from the application. Reporting tools can be developed and implemented so as to produce an automated maintenance schedule for all the utilities in the facility. Importantly, a selected utility can be visualized directly in the model. Others sensing technologies and BIM software and platforms (including IFC) need to be investigated.

A challenge to the 3 meter goal is determining what room the user is located in. The error is small enough to guide the personnel to the general area, but is also too large to guarantee the correct room. Therefore, a smaller accuracy should be achieved to address this issue. Further research is needed to take into account various environmental factors, such as corners, open rooms, or obstructions. These will all be addressed in upcoming research that will incorporate the the topology and geometry information of the BIM model with the presented algorithm.

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