Self-Corrective Knowledge-based Hybrid Tracking System Using BIM and Multimodal Sensors

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ABSTRACT

Researchers have recently devoted considerable attention to acquiring location awareness of assets. They have explored various technologies, such as video cameras, radio signal strength indicator-based sensors, and motion sensors, in the development of tracking systems. However, each system presents unique drawbacks especially when applied in complex indoor construction environments; this paper classifies them into two categories: absolute tracking and relative tracking. By understanding the nature of problems in each tracking category, this research develops a novel tracking methodology that uses knowledge of the strengths and weaknesses of various components used in the proposed tracking system. This paper presents the development

of a hybrid-tracking system that integrates Bluetooth Low Energy (BLE) technology, motion sensors, and Building Information Model (BIM). The hypothesis tested through this integration was whether such knowledge-based integration could provide a method that can correct errors found in each of the used sensing technologies and thereby improve the reliability of the tracking system. Field experimental trials were conducted in a full-scale indoor construction site to assess the performance of individual components and the integrated system. The results indicated that the addition of map knowledge from a BIM model showed the capability of correcting improbable movements. Furthermore, the knowledge-based decision making process demonstrated its capability to make positive interaction by reducing the positioning errors by 42% on average. In sum, the proposed hybrid-tracking system presented a novel method to compensate for the weakness of each system component and thus achieve a more accurate and precise tracking in dynamic and complex indoor construction sites.

Keywords

Bluetooth low energy (BLE); Building Information Model (BIM); inertial measurement units (IMU); location tracking; mobile sensing; data fusion;

1. Introduction

The use of tracking technology to detect the movement of personnel, materials and equipment is vital in any construction operation. Effective implementation of tracking algorithms for resources such as labor [1,2] and materials [3] can lead to better decision-making for construction management applications [4]. These applications include context-aware information delivery [5], progress monitoring [6], proximity visualization [7], and productivity analysis [8]. According to

the Health and Safety Executive [9], approximately 35% of accidents are directly/indirectly related to moving workers; 23% of accidents involving *moving workers* are caused by slips, trips, and falls, and 11% of worker accidents are struck-by accidents. In response to this, researchers have developed real-time tracking systems to monitor the indoor construction site safety condition with respect to identified potential safety hazards [10]. Furthermore, these tracking technologies are able to assist in collision avoidance [11], near-miss accident identification [2], proactive hazard signaling [12], and even building fire emergency response [13].

The nature of construction sites is, however, often complex and dynamic resulting from high volume of movement of both workers and materials as well as variability in building type, business type, and geographical location [14]. This can lead to many complications for tracking technology from both a hardware perspective and an algorithms perspective. From a hardware perspective, sensor setups used for tracking face several limitations in terms of range [15], measurement accuracy [16], signal strength fluctuation [17], interference [14], and cost [3] that prohibit their system deployment in actual construction environments, which are rapidly evolving. From an algorithms perspective, the tracking technique may need to combine data from multiple sensors [18], perform filtering on noisy data [19] and also take into account changes in the environment [20]. Moreover, certain tracking techniques require a time-consuming offline phase for performing the initial system setup and require static environments for reliable tracking, such as the fingerprinting method [21–23].

To overcome these sensor limitations, recent research has explored hybrid-tracking solutions that combine multiple sources of positioning information under an integrated framework. These recent research studies have attempted to use multimodal sensors, that is, sensors that measure different physical quantities, in order to achieve a more accurate tracking

solution. Despite these efforts, very few researchers has studied methods that explicitly use prior knowledge of sensor behavior in such integrated tracking systems. Identified behaviors of sensors form knowledge that can potentially correct errors in individual sensors when they are properly combined. To address this need for a more knowledge-intensive tracking system, this study develops a hybrid-tracking method incorporating Building Information Model (BIM) data, Bluetooth Low Energy (BLE) beacon signals and motion sensor measurements. This study takes advantage of knowledge of the nature of each source of tracking information: (1) BLE beacons provide absolute position information but are affected by high levels of noise, (2) motion sensors provide relative position information but are vulnerable to drift, and (3) building geometric information forms a new type of knowledge that can improve the tracking accuracy. This knowledge is utilized when integrating the different sources of tracking information under a probabilistic framework. The major hypothesis of this research is to test, by using knowledge-based error correction mechanisms, whether the integrated approach can correct errors developed in each of the sensors and thereby increase the overall reliability of the tracking system. The remainder of this paper will present, in order, the literature review, objective and scope, system design, case study and conclusion of the study.

2. Literature review

This section reviews the existing literature for the characteristics of different sensing technologies to build a knowledge base of the strengths and limitations of each type of sensor in terms of range, accuracy and reliability. The knowledge gained from prior work is critical to gaining an understanding the nature of each sensor component. In addition, the constructed

knowledge base will be used as a source of information for designing error-correction heuristics in the integrated tracking framework.

2.1. Sensing technologies for positioning

In the field of non-RSSI based tracking technologies, researchers have explored video sensing by applying numerous computer vision algorithms such as cascade of Haar features, mean shift, and the Lucas-Kanade methods that perform personnel tracking and equipment tracking [1,8,24].

Video sensing is, however, vulnerable to occlusions when multiple objects need to be tracked and when objects move in and out of video fields of view [8]. Inertial Measurement Units (IMU) are also a popular research domain for personnel localization through handheld or waist-worn devices [25,26]. However, IMUs struggle with a problem of error accumulation that leads to significant drift over time [26]. Furthermore, in indoor environments, magnetic interference can also negatively affect the heading direction inference [25].

An example of RSSI-based tracking technology is RFID, which has been studied in material and tool tracking for improving productivity and control processes in indoor construction sites [27,28]. However, RFID technology faces issues such as metal shielding, chip sensitivity and limited read range that lower accuracy and reliability for tracking applications [15,29]. Although RFID is an effective inventory tracking tool on construction jobsites [27], it does not meet the requirements for accurate, real-time tracking of dynamic entities in complex environments [30]. UWB is used for material tracking and activity-based progress tracking with advantages in power consumption, read range, and ability to work both indoors and outdoors [20]. It is, however, known to have issues with multipath interference, material-dependent

propagation, line-of-sight sensitivity, and difficulty in system deployment in changing environments [12,14,20,31].

A recent study used WLAN-based systems for performing labor tracking at a shield tunnel construction site by using a machine-learning technique called Fingerprinting [32]. It estimates positions using a pre-built map of approximate signal strength from each WLAN access point (AP) [21,32]. However, a major disadvantage of the fingerprinting technique is a lengthy offline phase where a site survey is carried out for hours or even days to build an RSSI fingerprints map [19,21]. Moreover, the fingerprint database represents the state of the site at the time of the database establishment, so this method may not operate properly in a changing environment, which is typical in a construction site.

BLE is a relatively new technology that was first released in 2010 and offers many advantages over traditional Bluetooth technology such as reduced power consumption, longer range, small form-factor, and lower latency [33–35]. BLE technology has the potential to overcome the previously highlighted problems in existing sensors for positioning. In comparison studies, BLE technology in the form of BLE beacons has been found to be more energy efficient and more flexible in terms of infrastructure deployment compared to the competing technologies [17,36]. As such, BLE technology can easily be integrated into hybrid-tracking frameworks alongside other sources of positioning information [37,38]. Similar to other wireless technologies, BLE is susceptible to fast fading and large Received Signal Strength fluctuations [17], but the lower cost and easier installation of BLE beacons allows the deployment of the system in larger numbers compared to UWB and WLAN. BLE technology has been researched in the construction domain in applications such as proximity sensing [36], but the full potential of the BLE technology in positioning has not yet been realized [32,33].

2.2. Integrated systems utilizing multiple system components

Recent research in tracking has also focused on integrated systems using multiple sensor technologies. Such hybrid systems can account for discrepancies in individual sensor readings through joint estimation methods; thus reducing tracking errors. For example, Li et al. [13] proposed a BIM-integrated localization system with Radio Frequency (RF) beacons. BIM information provided geometric context of the sensing area to minimize deployment effort and maximize localization accuracy for emergency response operations. Taneja et al. [39] developed algorithms to generate navigation models from industry foundation classes (IFC)-based BIM, and Taneja et al. [40] independently used an IMU sensor for relative tracking and Ekahau Wi-Fi sensors for absolute tracking, and combined each sensor with a map matching model to evaluate the performance of each system. Although they achieved forward advancement with this integration, their test results still present challenges such as a trap and drift from the IMU sensor and unreliable performance from the Wi-Fi sensor. Another recent study [41] used IMU with visual markers to improve the quality of indoor navigation. However, the placement of markers is a complicated task to perform in a busy, complex on-going construction site. Algorithmic studies [30,42] have also been conducted by exploring a combination of support vector regression/fingerprinting and Kalman filtering to achieve improved tracking. However, these systems may face practical issues in evolving construction sites. Park et al. [43] showed an innovative integration of multiple sensors, i.e. wheel encoders, motion sensors, UWB sensors and digital compass. Although the purpose of the study was to acquire an autonomous navigation system, which is different from asset tracking, the study showed a way to combine sensor data from multiple sources. The study effectively exploited

various components, but it presented several drawbacks: (1) the system required a complex configuration, (2) the tested environment was small compared to a real construction site, and (3) the commonly encountered drift problem in IMU was not resolved.

One approach to solving the drift problem is to impose constraints on the positioning estimate through alternative sensor measurements. Jiang et al. [44] used a hybrid-tracking system where a line detection routine on camera images was used to correct drift in gyroscope measurements. Although the camera-aided system operated well in an outdoor environment, it may not achieve the same level of accuracy in a cluttered indoor environment. On the other hand, prior information about the environment can also be used to constrain the motion output, such as using an indoor floor map to identify corridor boundaries [25] and using BIM to assist BLE-based tracking [38]. However, in these studies, the position estimation was still carried out mostly with a single type of sensor without significant integration of additional sensor inputs, which compensate for the shortcomings of sensors. On a similar note, Hu et al. [37] used BLE and accelerometers for an assisted positioning system but BLE was not integrated into the position estimation and the position was simply calculated using direct integration of accelerometer output [21]. One study considering the integration of BIM with commercially available RFID utilized a mobile cart with four large antennas for tracking [45]. The drawbacks of the study are that (i) the sensors cannot be attached on workers, so is not suitable for personnel tracking, (ii) the experimental layout with narrow corridors is only suitable for short range sensors, and (iii) the passive RFID system is not robust enough for complex indoor construction sites. On the other hand, Fang et al. [46] also integrated BIM with RFID but BIM was only used for visualization and did not assist in tracking.

Another common problem in tracking technology that can be mitigated through integrated systems is the unreliability of RSSI measurements. For example, the Zigbee-based tracking system [3] used a combination of Radio Frequency (RF) and ultrasound signals to eliminate multipath propagation and improve positioning accuracy. However, the utilized sensor network faces challenges with battery life and line of sight, so the system was developed and tested mainly for an outdoor environment. Without overcoming these challenges, it may not be a viable solution for an indoor tracking application especially for long-term deployment. On the other hand, Subhan et al. [47] used a combination of an offline map-building phase and an online trilateration phase in a Bluetooth network to improve the accuracy of tracking. The technique was successful in improving the tracking accuracy but still did not resolve the issue of the need of a time-consuming offline map-building phase for RSSI fingerprints.

Despite these previous research efforts in developing tracking systems by integrating multiple sources, they have insufficiently investigated systems in regards to the interaction of components. Table 1 summarizes recent state-of-the-art research in tracking compared with the proposed work. Many studies focused on improving the accuracy of tracking by introducing additional components to or by exploring algorithmic studies in tracking systems. So far, error correction of sensor data through integration of multiple system components has not been the focus of much attention.

Table 1

Methodological review of recent research

Method	Fang et al. [46]	Li et al. [48]	Park et al. [43]	Li et al. [49]	Faragher and Harle [17]	Li et al. [13]	Taneja et al. [39]	Li et al. [25]	Zhuang et al. [42]	Chai et al. [30]	Proposed Approach
Absolute positioning	O	O	O	O	O	O	X	X	O	O	O
Relative positioning	X	X	O	X	X	X	X	O	X	X	O
BIM for tracking	Δ	Δ	Δ	Δ	X	O	O	X	X	X	O
Error correction through integration	X	X	X	X	X	O	X	X	X	O	O

Δ : Used for visualization or path display only

A recent study [50] in data management presented a novel approach that combines advantages of various systems to reduce information load of data stream. The proposed study adopts the idea of using advantages of various systems in the development of an integrated tracking system; it combines data sources in a knowledge-based framework such that each source plays a specific role depending on its strengths and weaknesses. Therefore, this research studies a hybrid-tracking method incorporating (1) BLE beacons, which provide absolute positioning data, (2) motion sensors, which provide relative positioning data, and (3) BIM information, which provides a geometry-constraint map of the target area. This study will analyze the ability of the hybrid system to correct errors in individual sensors as well as the contribution of each type of sensor to the overall tracking accuracy.

3. Research objective and scope

This research creates and evaluates a hybrid-tracking system using knowledge-based error-correction mechanisms for use in an indoor construction environment. To develop a hybrid-tracking system, this research integrates BLE, motion sensors and BIM. This integration allows

the system to collect and thus leverage data from multiple sources for improved tracking performance. The major hypothesis of this research is to test whether a knowledge-based integration can correct errors developed in each of the sensors and thereby increase the overall reliability of the tracking system. The integrated tracking system should be able to (i) correct fluctuating signals from the absolute positioning system (BLE component), (ii) correct drift in the relative positioning system (motion sensor component), and (iii) account for building geometric constraints by using BIM information. The scope of the study includes the development of the integrated tracking system, a full-scale field experiment, and the subsequent analysis and discussion regarding improved tracking reliability through the system integration.

4. Methods

4.1. System architecture

To achieve the research objective, this research took an integrated approach in the development of a tracking system. The developed tracking system is composed of three major components including 1) a BLE system, 2) motion sensors, and 3) a mobile BIM model (refers to a BIM model that is converted to a format that runs in mobile devices such as smart phones and tablets). The BLE component uses received signals to estimate positions of a moving target. Such a signal-based tracking component is good for coarse movement tracking based on absolute positions calculated using the received signals. On the contrary, the inherently noisy characteristic of RSSI signals results in unreliable position estimations. To overcome this limitation encountered in the BLE tracking component, this research utilized motion sensors. Motion sensors provide an estimation of movement relative to a previously known position, which improves the reliability of position estimation. As a third component of the system, BIM

plays an important role in improving the quality of position estimation. Building elements in a BIM model contains important geometric information that transforms to map knowledge. Such information forms geometric boundaries, which can improve the position estimation. Figure 1 presents a system overview showing each of the system components and integration into a single software platform.

Fig. 1. Tracking system overview

Using BLE signal communication theory, a novel localization approach was designed and implemented based on a probabilistic model. This probability-based localization is reinforced by motion sensors that are already built-in on a mobile device (e.g., smart phones, tablets). With the integration of a BIM model, map knowledge is further added to the system to prevent false

detection of movements using boundary constraints. An example of tracked output with ground truth and estimated paths is shown in Figure 1.

4.2. BLE sensors

One of the major advantages of BLE lies in its new network topology. Classic Bluetooth technology was based on ad-hoc piconets, which use a master device and up to seven slave devices. In contrast, BLE technology uses an innovative advertising and scanning method, which does not limit the number of devices for communication; BLE does not require pairing with other BLE devices to advertise data packets and scan data packets from other BLE devices. For this reason, many more devices, although the number is not defined, can simultaneously communicate with multiple master devices; based on our lab tests, more than 30 BLE sensors (BLE version 4.0) can be simultaneously detected by an iPhone as well as an iPad.

Through this multi-connection between the BLE sensors and a mobile device, RSSI data is collected. Eq. (1) and Eq. (2) present a relation between RSSI and distance between the beacon of interest and the mobile device, which converts the collected RSSI into a useful form for further computation [51,52]. In Eq. (1), the parameter “n” is a pass loss constant that varies depending on the surrounding environment, so its value is estimated with on-site calibration. The distance measurement from a BLE sensor represents a 3D distance from the BLE sensor. As the elevations of the BLE sensors are known from the system setup, this 3D distance is then decomposed into horizontal distance and vertical distance using trigonometry [53], which allows a straightforward conversion from 3D distance to 2D distance. Note that an actual distance used in Eq. (2) is defined as the 3D Euclidean distance between a candidate coordinate and a BLE

sensor of interest, and an estimated distance used in Eq. (1) is the 3D distance estimation computed from measured RSSI data.

In most cases, unreliable signals exist resulting from occlusion, signal degradation, and other negative environmental effects, which are considered as intrinsic errors of RSSI [54,55]. To minimize the effect of unreliable RSSI measurements, this research takes a probabilistic approach that was developed in the authors' previous research [56]. A normal distribution model (Eq. (3)) is used to assign weights to each of the distance measurements. This assignment is based on the relationship between an actual distance and an estimated distance for a given candidate coordinate. Given the relationship between the distance and the RSSI measurement, one variable can be calculated if the other variable is known. During the execution of the algorithm, multiple candidate points are generated. Then, each point is evaluated based on Eq. (3) for all detected beacons, and the results are aggregated. As a result of this, the point with the highest evaluation is selected for the next position estimation (Eq. (4)). This probabilistic evaluation is effective in handling line-of-sight issues common to RSSI-based tracking systems since the raw RSSI values are not used directly but combined with independent sensor measurements to generate an aggregate position estimation. Thus, the obstructed BLE signals can be accounted for using the unobstructed signals received by other sensors.

$$d_e = 10^{-\frac{abs(RSSI_1) + RSSI_r}{10n}} = f(RSSI_r; RSSI_1, n) \quad (1)$$

$$RSSI_e = -10n \log(d_a) - abs(RSSI_1) \quad (2)$$

$$P(RSSI_e) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(RSSI_r - RSSI_e)^2}{2\sigma^2}} \quad (3)$$

$$(x, y)_{BLE} = \underset{(x,y) \in XY}{\operatorname{argmax}} \left(\sum_{all \text{ beacons}} P(RSSI_e) \right) \quad (4)$$

d_e : estimated distance
 d_a : actual distance
 $RSSI_e$: estimated RSSI
 $RSSI_r$: received RSSI
 $RSSI_1$: RSSI measurement at 1 meter
 n : path loss constant
 XY : all pairs of (x,y) coordinates

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297 Figure 2 illustrates an example of algorithmic assessment with three distance
 298 measurements. The example is a simulated 2D environment where the plot represents a top-down
 299 view of the world. X and Y are Cartesian coordinates in the 2D space and the dotted circle
 300 represents equidistant points from the beacon origin where the radius is the distance estimated by
 301 beacon's RSSI values. The simulated situation shows two beacons with reasonably accurate
 302 distance estimation and one beacon with significantly degraded distance estimation. Through
 303 probabilistic analysis of multiple candidates of coordinates, the algorithm can identify unreliable
 304 signals and minimize their effects in the position estimation; in the example, the distance
 305 estimation from Beacon 3 is considerably distorted, but the result of the position estimation is not
 306 affected by the distorted data.

307

Fig. 2. Example of the algorithmic evaluation

The probabilistic estimation of position can be visualized in 3-D as shown in Figure 3 that is based off of the same data set as in Figure 2. Figures 3a, b and c depict the probability distribution of the measurement from each beacon (see the coordinates and distance measurements for a matching pair), whereas Figure 3d shows the aggregated probability distribution. As each point is evaluated, the algorithm keeps track of the most likely point to obtain an absolute position estimate. In this case, the given signal inputs together with the geometric information of the beacons find the most likely point as (0.7, 5.8) shown in Figure 3d. Thus, using the RSSI of communication signals between the BLE sensors and a mobile device, an absolute position of the mobile device is obtained.

Fig. 3. Probabilistic evaluation of points: a), b) and c) are individual measurements, and d) is the aggregated result

4.3. Motion sensors

Motion sensors are usually equipped with three types of sensors, namely, gyroscopes, accelerometers, and magnetometers. Among the three different sensors, only gyroscopes and accelerometers are used in the developed system because data from magnetometers can be easily distorted by materials containing ferromagnetic, iron, nickel, cobalt and manganese. The proposed system utilizes built-in motion sensors in the tested iPhone 6 and iPad air.

These additional motion sensors provide heading directions and the step count at each time of estimation, which are fused with the BLE-based position estimation. With the obtained heading direction and the number of steps at each time interval, a relative movement of the target

with respect to the previous position is computed, and the corresponding position is obtained (Eq. (5)). This estimation serves as a relative position estimation whereas the estimation from the BLE component serves as an absolute position estimation.

$$(x, y)_{i_{motion}} = (x, y)_{i-1} + (\Delta x, \Delta y)_{motion} \quad (5)$$

4.4. Use of BIM

The developed tracking system also uses BIM as additional information for tracking. The algorithm takes advantage of building geometry (e.g., walls) to improve the accuracy of location estimation. BIM geometry and object information are extracted from a BIM model into a XML file and imported into the mobile system. Since this study is only concerned with 2D tracking within a floor level, the (x, y) component is extracted from the original (x, y, z) coordinates of the 3D geometry. This information is used as map knowledge in the tracking module, which provides geometric constraints that can help minimize false movements in tracking. Examples of geometric constraints are walls and doors. Any improbable movements that pass through geometric boundaries are eliminated; points that fall into this category are ignored in position estimation. However, during the position estimation, there are certain situations where BIM constraints have to be relaxed to allow for movement from a space to another space such as a door opening or a narrow column. For example, a buffer was applied to doors to allow an extra space to account for the positioning uncertainty.

4.5. Knowledge-based error correction mechanisms

Figure 4 illustrates a framework of the knowledge-based error correction method used in this study. The framework uses a knowledge base consisting of BLE sensor (an absolute tracking

component) characteristics, IMU sensor (a relative tracking component) characteristics and semantic map knowledge from BIM object property data and geometric constraints. The main knowledge base used in the framework is as follows:

- BLE beacons provide absolute position information
- Motion sensors provide relative position information
- An absolute positioning system lacks the capability of correcting fluctuation because of lack of knowledge of moving trends for instant moments; but it provides valuable knowledge of moving trends for a period of time, which can be deduced from overall changes in movements.
- A relative positioning system struggles with a drifting problem because of the error accumulation, which our method fixes by interpreting the trend of movement by an absolute positioning system.
- BIM object property and geometric information can provide semantic map knowledge that improves the tracking accuracy of both absolute and relative positioning data. E.g., workers can only pass through a door, not wall and large openings.

Fig. 4: Rules and Knowledge-based error correction system

The sensor characteristics include quantitative data of sensor behavior. For example, BLE sensor data struggle with high levels of fluctuation, whereas motion sensors data are vulnerable to drift. The error-correction mechanism is driven by a rule-based module. The rule-based module examines the sensor data for specific error scenarios that necessitates error-correction steps. Then, the final stage takes effect whenever a condition for the error correction is met, which is responsible for making decisions in the data fusion process of the positioning algorithm. Some examples of the output decisions are assignment of relative weights of the sensor measurements, arbitration for conflict scenarios and execution of reset procedures under special circumstances.

In fusing the estimations from the BLE and motion sensor components, the algorithm adopts a low-pass filter as shown in Eq. (6). The use of a low-pass filter with our approach presents several benefits; 1) it offers mathematical simplicity for a real-time application, and 2) it

does not require any assumptions in error modeling, which is constantly changing in the measurements of the motion sensor.

$$(x, y)_i = (1 - \alpha)(x, y)_{i_{BLE}} + \alpha(x, y)_{i_{motion}} \quad (6)$$

Upon the onset of the tracking application, the three components (beacon sensors, motion sensors, and map knowledge) dynamically interact together to estimate the target's location at each step. The most important aspect of this integration is their knowledge-based error correction, which is illustrated with a flowchart in Figure 5. In normal conditions, where no discrepancies are found between the measurements of the BLE and motion sensors, the results from the motion sensors and the BLE sensors are fused as explained in Eq. 6. However, as tracking progress is made, the motion sensors gain accumulated errors, which lead to a discrepancy in the position estimation. When the final estimation indicates a significant difference between the coordinate estimations from the BLE and motion sensors, the system initiates a heuristic error correction step through knowledge-based decision-making. The system checks whether this discrepancy is continuously detected; a continuous detection of this phenomenon is important because it indicates that the system is biased by a persistent error. The system then assumes this error is caused by an accumulation of errors in the motion sensors and proceed with the knowledge-based error correction mechanism as shown with "drift error correction" in Figure 5; an error correction is applied to the drift by correcting the heading direction of the motion sensors.

Fig. 5. Flowchart showing the interaction of the system components

Another example of a discrepancy that is related to “semantic navigation error correction” in Figure 5 is involved with map knowledge (e.g., when the user is predicted to walk towards geometric boundaries). In this case, the availability of map knowledge allows a heuristic system evaluation. The position estimations near a wall are considered less reliable, so smaller weights are assigned to nearby points. However, a problematic situation occurs when the subject moves along a wall that includes an opening such as a door and is erroneously predicted to enter another room. An additional check is put in place to detect such a “trapped situation”. For example, once there is a strong indication that the subject is in fact in a different room, the tracking algorithm uses current BLE beacon data to update the latest position instead of relying on the trapped previous position. On the other hand, if this situation is not detected, the tracking algorithm will proceed as normal and directly fuse the position estimations from BLE beacons with position estimations from the motion sensor.

In the proposed hybrid-tracking framework, such knowledge-based corrections are necessary when conflicts occur between different sources of tracking information. Demonstration of these interactions is further discussed in the validation section with the field tests conducted at a real-world building construction site.

4.6. Sensor calibration

For BLE beacons, the conversion from RSSI values to distance involves several environment-dependent parameters such as “ n ” and “ $RSSI_1$ ”. The values of these parameters are estimated through on-site calibration, which involves the following steps: (i) repeatedly sample the RSSI values at several fixed distances, which are known beforehand, and (ii) calculate the optimum parameter estimates given the measured RSSI according to Eq. (1).

Fig. 6. Data collection from the motion sensors and calibration

Additionally, the motion sensor component also requires calibration for the purposes of step detection. Each person has a different walking profile, and this variability needs to be captured in the step detection algorithm accordingly. To account for this, personal calibration is provided to obtain parameters, which define a walking profile. Figure 6 displays collected acceleration data during the calibration process. This calibration is performed to compute two threshold parameters, 1) step threshold and 2) time threshold. The calibration routine involves having the user input the actual number of steps into the mobile device and optimizing the threshold parameters based on the number of steps. The calibration is especially important for the following reasons: 1) the step threshold is to detect false movements, which are not triggered by walking. They include changes in accelerations due to turns, vibrations from hands, and any

other subtle movements. Peaks and valleys are tracked during the operation. When the difference between a peak and valley exceeds the step threshold, a step is counted. 2) The time threshold also plays a crucial role in removing false movements that correspond to large changes in accelerations. An example of such a case is a time in which a person makes a turn while walking. Because these two movements produce large changes in acceleration but happen at slightly different times, the step detection algorithm will falsely count the movements as two different steps. Therefore, individual calibration for the step threshold and time threshold is necessary for eliminating these false detections in the step detection algorithm.

5. Case study

5.1. System set-up

Validation of the proposed system was performed at a building construction site located in Atlanta, GA (Figure 7a). Figure 7b shows an example of a tracked subject whereas Figure 7c shows samples of installed BLE beacons. Although the image in Figure 7a was taken when workers were not present for a clear view of the site, the tracking experiments were in fact carried out during the hours of construction operation, when many construction activities were occurring and potentially presenting obstructions to the tracking process. This allows the system performance to be critically evaluated with respect to multipath interference and line-of-sight issues, which occur in dynamic environments common in construction sites. Figure 8 shows the two-dimensional map (27.4 x 39 meters) of the site testbed, where 20 BLE beacons (marked as blue x's) were deployed over beams, girders or pipelines (Figure 7c). The initial plan for beacon deployment was to install beacons at approximately 5-meter intervals. The complex indoor construction site, however, presented obstructions to the beacon installation process and required

470 the system to be much more coarsely deployed. The beacon deployment density after re-planning
471 was 57 m^2 per sensor, although the initial plan was 25 m^2 per sensor. Note that real construction
472 sites may not allow the system deployment to be as desired, so the ability of a tracking system to
473 adjust its deployment layout as required by the complex site is important.

Fig. 7. Construction site testbed

Fig. 8. Two-dimensional view of the test site

5.2. Experiment

The experiment involves two scenarios for tracking the motion of a test subject across the building construction site. The designed scenarios were intended to introduce complex movements by including a number of turns rather than simple straight back and forth movements. Testing complex movements is essential to assess the system's reliability for realistic construction applications; simple straight back and forth movements are not enough to simulate the nature of construction sites characterized by multipath effects and signal degradations. In addition, the major problem of drift in motion sensors will not be apparent with simple straight-line movements. However, with the inclusion of turns, the BLE signal communication becomes more complicated, and significant accumulation of error from motion sensor drifts can occur. For these reasons, complex movements involving multiple turns at various angles and movement in and out of rooms were introduced into the test scenarios to create relatively more difficult situations for tracking and to assess the capability of the system with respect to tracking accuracy.

Figures 9 and 10 show the tracking results overlaid on a 2D map of the test site for Scenarios 1 and 2 respectively. The traveled distance on the path in the first tested scenario was 99.7 meters long including six $60^\circ \sim 120^\circ$ turns while the traveled distance in the second scenario was 99.4 meters with one 180° turn and seven $60^\circ \sim 120^\circ$ turns. The second test scenario also included movements in and out of rooms to investigate the effect of integrating BIM into the tracking system. In total, about 8,000 data points and nearly 200 position estimations were obtained for each scenario for analysis.

Fig. 9. Tracking results for Scenario 1

Fig. 10. Tracking results for Scenario 2

In the lower right corner of Figure 10, it may be observed that the “BLE” tracking result differed slightly from the “BLE + BIM” tracking result even though there are no violations of BIM constraints present. This discrepancy is because the two trajectories are generated separately from the tracking algorithm and the probabilistic framework used resulted in random variations. However, since the experiment includes two different scenarios that involve many complex movements of the test subjects, the experimental results are expected to capture a substantial amount of these random variations. In addition, the large volume of data collected (8,000 data points and 2,000 position estimations) gives statistical significance to the following analysis of position error.

6. Results

Data collected at the site was analyzed component-by-component in three different cases as follows: 1) BLE sensors only, 2) BLE sensors and BIM, and 3) BLE sensors, BIM, and IMU sensors. For each of the three cases, the estimated positions were computed, and the accuracy

was determined based on the Euclidean distance error between the estimated positions and the ground truth positions. The ground truth positions were calculated based on logged time information as each subject walked along the designed paths and based on the assumption that the test subject walks the designated paths at constant speed. Tables 2 and 3 show the statistics of position errors (maximum, minimum, average, and standard deviation) for Scenarios 1 and 2 respectively. Table 4 further shows a comparison of average $\pm$ standard deviation position error for the both scenarios. In Scenario 1, the inclusion of BIM decreased the average position error from 2.31 meters to 2.26 meters while the addition of IMU decreased the error to 1.15 meters. Similarly, the inclusion of BIM in Scenario 2 decreased the average position error from 3.21 to 3.07 meters while the addition of IMU decreased the error to 2.03 meters.

Table 2

Position Error for Scenario 1

Position Error (m)	BLE	BLE + BIM	BLE + IMU + BIM
Maximum	6.94	7.50	3.23
Minimum	0.02	0.06	0.01
Average	2.31	2.26	1.15
Standard Deviation	1.61	1.62	0.72

Table 3

Position Error for Scenario 2

Position Error (m)	BLE	BLE + BIM	BLE + IMU + BIM
Maximum	8.36	8.85	4.51
Minimum	0.09	0.04	0.01
Average	3.21	3.07	2.03
Standard Deviation	1.97	1.88	1.22

Table 4

Comparison of average $\pm$ standard deviation position error for both scenarios

Scenario	BLE (m)	BLE + BIM (m)	BLE + IMU + BIM (m)
1	2.31 ± 1.61	2.26 ± 1.61	1.15 ± 0.72
2	3.21 ± 1.97	3.07 ± 1.88	2.03 ± 1.22

The individual components of the proposed hybrid-tracking system can be analyzed with respect to their contribution to the overall position estimation accuracy. Table 5 presents the quantitative improvement of the BIM and IMU components compared to the baseline BLE results. The inclusion of IMU into the integrated system proved to have a large impact on accuracy since the position error decreased by 42% on average. The inclusion of IMU also improved precision significantly since the standard deviation of position error decreased by 45% on average. Figure 11 displays an event of false movement in each scenario. As in the figure, the false movements are discarded, and the new position estimation step is recalculated followed by each false movement.

Table 5

Improvement of positioning accuracy for each component

Scenario	Percentage decrease by BIM		Percentage decrease by BIM + IMU	
	average position error	standard deviation of position error	average position error	standard deviation of position error
1	2%	0%	49%	55%
2	4%	5%	34%	35%
Overall	3%	2%	42%	45%

Fig. 11. Detection of false movement near geometric boundaries using BIM

To highlight the ability of the proposed methodology to reduce errors, Figure 12 provides the tracking results in plots of errors over time. As shown in the graph of position error over time for both Scenarios 1 and 2, the error does not accumulate past 3 meters near the segment 3 for Scenario 1 and 4 meters along the segments 6 - 10 for Scenario 2. However, with the error correction mechanism in the interaction of the system components, the error drops back down after a few seconds. In Scenario 2, a clear drift is observed, which cannot be corrected by a single sensor component. This correction is due to the integration of the system components between BLE beacons, motion sensors and BIM data, where corrective steps are taken at each instance when discrepancies are detected between different sensor measurements.

Fig. 12. Tracking results with plots of error over time

7. Discussions

This study presented the development of a hybrid-tracking approach using knowledge-based error correction mechanisms and demonstrated its performance through field trials. The test results suggest that the hybrid approach showed the ability to reduce the errors developed by each of the sensors. The path results showed that the integration of both the motion sensors and the map knowledge eliminated the problem of high fluctuation in an absolute positioning system (i.e., BLE beacons). In addition, the statistical results and the error plots demonstrated that the accumulation of errors, which is the major challenge in a relative positioning system, did not

occur in the tested system. Although the inclusion of map knowledge from BIM represented a comparatively small improvement ($\sim 3\%$) in the positioning accuracy, it remains as a vital component in the integrated tracking system since it helps restrict the drift in position estimates. The end of Path 5 in the second scenario caused a significant drift of the position, which was not found in the first scenario. Although such a drift was undesired, the knowledge-based error correction mechanism was clearly observed with this scenario as the error was fixed by the interaction of the system components.

The knowledge gained in this study is that the inclusion of IMU proved to have a large impact on accuracy while the inclusion of BIM represented a relatively small gain in accuracy but remained a vital component in reducing drift. The major purpose of the field experiments was to demonstrate the ability of the hybrid system to correct errors, which developed from each of the sensors. For this reason, the number of experiments is not so critical as long as the hybrid system has such a generalized ability to correct errors as demonstrated from the tests. The proposed tracking system is, however, subject to a few limitations. The positive effect of the interaction in correcting the drift in IMU partially relies on the position estimation by the BLE component; the overall movement of the test subject needs to be primarily observed by the BLE component; if the BLE component, for some reason, produces unreasonable results, the positive effect of the system interaction may not be observed, and the position estimation may be less accurate. The motion sensor component of the tracking system is also subject to some operational limitations. The motion sensors in tested mobile devices that are freely reoriented by a user during the course of position tracking produced noisy data, and this presents a challenge in obtaining reliable heading direction and step counts. For this reason, the test subjects were required to hold a mobile device at a fixed position and orientation with respect to the body using

such as belt clip and armband throughout the course of the experiment. In addition, the installation of BLE beacons needs to be strategically planned based on the building design and construction schedule to reduce the relocation of the initially deployed BLE beacons.

8. Conclusion

This study discussed the investigation of a hybrid-tracking system that integrates Bluetooth Low Energy (BLE) technology, motion sensors, and BIM. By understanding the nature of problems in each tracking category, this research developed a novel tracking methodology that uses knowledge of the strengths and weaknesses of various components used in the proposed tracking system. The three components dynamically interact together in a probabilistic framework to estimate the target's location at each step. The tested hypothesis in this integration was whether the integrated approach can correct errors developed in each of the sensors and thereby increase the overall reliability of the tracking system. The proposed system was validated through field experimental trials conducted in a full-scale indoor construction site. Comparative analysis of collected data indicated that the integration of map knowledge demonstrated the promising capability of correcting improbable movements whereas the integration of motion sensors provided higher accuracy by decreasing the positioning error by 42% while reducing the fluctuation of the tracking results by 45% on average. In addition, the error analysis indicated that errors in the motion sensors did not accumulate but were reduced through the system interaction, which contradicts the typical behavior of error accumulation in motion sensors. In sum, the proposed hybrid-tracking system demonstrated the ability to compensate for the weakness of each system component and to achieve low-drift, high precision, and accurate tracking in dynamic, complex indoor construction sites.

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