Case Study

Signal Processing and Alert Logic Evaluation for IoT-Based Work Zone Proximity Safety System

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Abstract: Construction projects are dynamic by nature because of continuously moving resources such as heavy equipment and workers. This nature necessarily results in proximity hazards, especially on a large-scale construction site. Especially, struck-by accidents still account for about 38% of the total injuries in the US construction industry. Although there have been several efforts to mitigate the hazards, the statistics show that the hazards still persist. To provide a practical solution to this problem, this study proposes an Internet of Things (IoT)-based proximity warning system that provides an alert to workers whenever they are close to heavy equipment. The system includes equipment protection units (EPUs), personal protection units (PPUs), and Bluetooth low energy (BLE) beacons. A framework of signal processing and alert logic was developed to estimate the distance between PPUs and EPUs and to activate alerting modules timely. By calculating the distance based on the signal strength using a particle filtering method, EPUs and PPUs provide auditory and vibration alerts to equipment operators and workers when they are in an alert range. Also, practical alert logic was developed based on the site worker's feedback. This study validates the system performance with different signal processing methods and alert logic through five real-world field tests. The system achieved a precision, recall, and F1-score of 89.21%, 97.45%, and 0.931 from the field tests, respectively. Also, positive feedback was obtained from the participating workers. The proposed IoT-based proximity warning system has a high potential for a practical solution to proximity hazards in actual construction sites. DOI: 10.1061/JCEMD4.COENG-12417.

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Introduction

Construction projects inherently involve various resources moving dynamically, such as heavy equipment and workers. The dynamic nature of construction projects has exacerbated a variety of hazards in construction sites as the sites have been enlarged and complicated. Due to this tendency, in 2020, 21.2% of the fatal injuries in the private industry sector were in the construction industry according to statistics reported by the US Department of Labor (2021). Especially, struck-by accidents still accounted for about 40% of the total 1,008 fatal injuries in the US construction industry in 2020 (US Department of Labor 2021).

Although advances in technologies can be used for safety management, safety issues in jobsites have remained unsolved. Traditionally, safety measures on jobsites mainly focused on the lagging information obtained after accidents. Here, the lagging information is defined as historical information generated after accidents happen (Hinze et al. 2013). For example, safety hazard statistics and corresponding safety practices can only be available after a certain number of accidents are accumulated. Once an accident occurs, the safety manager collects information such as the type of the given tasks, accident context, type of related objects, and safety-related statistics. After sufficient information is collected, conventional safety practices, including safety training, safety education, and utilization of task-specific personal protective equipment (PPE), are implemented based on the accumulated lagging information. Despite the widespread utilization of those practices in construction projects, they are not an effective way to properly allow workers to take proactive actions against a dangerous situation. As the lagging information does not contain contextual information that the workers are experiencing, the aforementioned practices cannot show the best performance in a dynamic situation. To overcome this problem, the leading information is utilized for proactively recognizing the hazards on a jobsite. As opposed to the lagging information, the leading information is defined as information generated on a particular jobsite on a real-time basis (Kim et al. 2017b). For example, the leading information includes the current surrounding hazards such as moving objects, holes, pits, and electrical wires. If workers can find and obtain this information, proactive actions can be taken, and the hazards can be mitigated in time.

While several research efforts have been made to provide proactive information to workers to prevent struck-by accidents, practical solutions are still lacking. Common practical challenges in existing efforts are the lack of infrastructure for monitoring a construction site that has not only effectiveness but also scalability. For example, a system that utilizes wireless communication such as radio frequency sensing and global positioning system (GPS) technologies requires a cumbersome infrastructure or expensive sensing devices to enable the system to detect and track the movement of objects of interest (Brilakis et al. 2011; Kim et al. 2015, 2017b). Likewise, a system that uses vision cameras for monitoring objects requires numerous cameras covering a large-scale construction site to reduce blind spots (Park et al. 2016b). Installing and maintaining many cameras in a changing dynamic construction site is not a

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feasible solution. In addition, vision-based systems require higher computation cost and data transmission capacity (Huang et al. 2021). This indicates that the construction industry still needs a practical solution that can reduce the risk of a struck-by accident.

This study proposes a proximity safety sensing and alerting system that provides an alert to workers and heavy equipment operators when they are in proximity hazard situations by using an Internet of Things (IoT) technology with the least required infrastructure. Multiple field tests were conducted in actual construction jobsites to validate the performance and utility of the system. The system estimates the distance between equipment and workers by using Bluetooth low energy (BLE) sensors attached to the equipment. By calculating the distance with the signal strength of the sensors, the system detects the workers at a certain distance and provides alerts to the equipment operator and the worker simultaneously. Meanwhile, all data related to the hazard, including sensor signal, worker identification number, and equipment identification number, are uploaded and stored in a cloud server. Then, the data are visualized in the web user interface so that the safety manager can monitor the safety condition of the jobsite on a real-time basis. To validate the system, the system is implemented and deployed on different construction sites. From these field tests, the performance of the system is evaluated under uncontrolled environments, and lessons about implementing the system on an actual jobsite are investigated.

Literature Review

The proximity safety sensing and alerting system provides a warning to equipment operators, workers, or both when a relative distance between entities is within a predefined range so that they can proactively recognize a hazardous situation surrounding them. Various types of warnings can be utilized, including visual, acoustic, and vibratory signals. One of the most dominant features that categorize proximity safety sensing and alerting systems is calculating distances between entities of interest using different modalities. Based on the calculated distances, the system can decide whether it should provide a warning or not. In addition, proximity safety sensing and alerting systems can be characterized by communication methods for transferring, storing, and processing data. In this context, this section reviews existing proximity sensing and alerting techniques in construction safety.

In general, proximity safety sensing and alerting systems can be classified according to methods of deriving a spatial relationship between entities of interest, which include GPS, vision-based monitoring techniques, and wireless sensing technologies. Each method utilizes different modalities to calculate distances between entities and has distinguishable advantages and disadvantages.

GPS uses triangulation to determine the absolute location of a receiver in three-dimensional coordinates. The proximity between the objects of interest, such as workers and heavy equipment, can be measured by using the absolute locations of the objects (Pradhananga and Teizer 2013; Razavi and Haas 2010; Song et al. 2006; Wang and Razavi 2016; Wu et al. 2013). A framework for monitoring a collision between large haulage equipment in dam construction was developed based on its location derived from GPS (Wu et al. 2013). Speed and heading direction, as well as two-dimensional coordinates, were considered to reduce false warnings in measuring proximity between objects (Wang and Razavi 2016). However, the signal strength is vulnerable to factors such as climate, ionosphere, troposphere, and electromagnetic waves. It also requires a wide field of view and fewer lines of sight occlusion near the receiver. Moreover, expensive investments for additional hardware are required for high-accuracy localization (Pradhananga and Teizer 2013). Wang and Razavi (2016) tried to fuse other sensor data such as IMU with GPS because it helps improve accuracy. However, they considered only one piece of equipment and worker; therefore, other important factors such as site layout and equipment operations were not taken into account. Also, the experiments in this study were conducted in a controlled environment. Thus, it did not reflect real-world scenarios involving multiple equipment and workers.

The vision-based monitoring technique uses one or multiple and two or three-dimensional cameras to identify objects without any additional device such as positioning tags or other sensors. The spatial relationship between objects of interest is derived by detecting and localizing the objects based on their pixel intensity and their changes in two or three-dimensional space. Then, proximity can be calculated and measured based on the spatial relationship from images. By using an image-based object tracking algorithm, object locations, categories, velocities, and violations of safety rules were identified to assess safety conditions in earthmoving and surface mining activities (Chi and Caldas 2012). A vision-based safety assessment system using fuzzy inference logic was developed to monitor struck-by accidents on construction sites (Kim et al. 2015). Monocular images were utilized to track the locations of multiple objects, and their proximity and crowdedness were used to evaluate their safety levels. The fuzzy inference-based safety assessment system was integrated with augmented reality in a wearable device so that the derived results can be intuitively visualized to improve workers' recognition of hazards (Kim et al. 2017b). In addition to the applications with fixed cameras, an unmanned aerial vehicle (UAV)-assisted proximity monitoring system was developed with a deep neural network-based object localization (Kim et al. 2019, 2020). However, it is impractical in terms of power supply and unsafe to keep a UAV over construction workers and equipment long period of time. Vision-based monitoring techniques have advantages in the automation of detecting and tracking objects due to the advance in image classification algorithms (Fang et al. 2018; Kim et al. 2017a) and in the capability of recognizing multiple objects without any additional tag or sensor. However, image sensing techniques are difficult to perform well under harsh outdoor circumstances such as dust, rain, snow, or night environments. Also, it provides a restricted result in line-of-sight occlusion (Kim et al. 2017b).

The most widely used wireless sensing technologies in construction include radio frequency (RF) sensing, ultrawide band (UWB), BLE, ultrasonic, and magnetic field. Basically, these technologies measure the distance between objects by using the signal strength of tags or sensors mounted on objects. Based on the measured distance, a warning is provided to users, e.g., operators and workers, for informing them of approaching objects when the objects are within the predefined warning range (Fang et al. 2016; Ju et al. 2012; Lee et al. 2012; Park et al. 2016b). Different types of wireless sensing technologies, including RF identification (RFID), Bluetooth, and magnetic field, were evaluated in terms of the accuracy of measuring the warning distance and false warning rate in the empirical experiment (Park et al. 2016b). In this study, it was found that the proximity sensing system utilizing Bluetooth outperforms others in terms of installation, cost, and time for calibration while showing similar performance. UWB emits short pulses with low power and filters out the reflected signal to estimate accurate location results for distance calculation (Cho et al. 2010; Han et al. 2019; Maalek and Sadeghpour 2016). RF-based systems can get distance information by only tracking the signal intensity of tags. Also, it has little impact on the occlusion problem and illumination conditions (Zhang et al. 2017). However, it is limited in indoor environments due to multipath effects and also observed metal interference (Cho et al. 2010). BLE is a wireless technology capable of exchanging data, communicating over short distances, and connecting to several devices in real-time simultaneously through an ad-hoc network. It has been widely used because of its rapid connectivity, low-cost hardware, low energy consumption, and minimal infrastructure requirements. Bluetooth has been successfully evaluated for many applications, and the capabilities of this system could potentially detect and alert workers during hazardous proximity situations (Park et al. 2016b, 2016b). An ultrasonic-based sensor system and a pulse radar-based system have been developed for the prevention of backing accidents in construction work zones (Choe et al. 2014) with a formalized framework for a sensor-based proximity sensing system proposed by Choe et al. (2013). Magnetic field sensing technology has been used in underground mining, which showed relatively good performance among the other compared devices. However, the disadvantage of the magnetic field device is that the installation and setup are difficult, the cost is relatively high, and there is no calibration ability, meaning it requires a change of antenna to modify the range limit, which adds more cost (Park et al. 2016b). Table 1 shows the summary of the literature review on proximity alerting systems with different sensing types.

Among various proximity measuring techniques, this study deployed a BLE-based proximity safety sensing and alerting system for several reasons. First, a BLE-based system has appropriate scalability for deploying the system on a large-scale construction site. Second, it does not require a heavy infrastructure to communicate between entities. The system can be deployed with a minimum infrastructure that can be easily carried like a smartphone or a cellular hotspot. While other technologies require cumbersome equipment or devices to cover a large-scale jobsite, a BLE-based system can cover a large-scale jobsite by adding small-sized BLE beacons. Moreover, the sensor calibration process is only required once at the beginning of implementing the system. Last but not least, compared to other wireless sensing technologies, BLE shows robust and reliable accuracy in measuring proximity (Park et al. 2016b). This feature is essential for developing a practical solution to proximity hazards in construction sites. For these reasons, BLE was selected as a communication protocol of the proposed proximity safety sensing and alerting system in this study.

System Architecture

The proximity warning system uses two types of devices: personal protection unit (PPU) and equipment protection unit (EPU). A PPU is embedded in a worker's safety vest and an EPU is attached to the equipment. PPUs and EPUs use a multiwireless-protocol microprocessor that supports WiFi, Zigbee, and Bluetooth. Fig. 1 illustrates the overall architecture of the proposed proximity warning system. In Fig. 1, three types of data flow do not interfere with each other.

PPUs sense the signal strength from the Bluetooth beacons that are attached to equipment and periodically broadcast signals with 10 Hz frequency and estimate the distance to nearby beacons (Blue dash lines in Fig. 1). A PPU checks if the worker who carries the PPU is within a specific range to equipment from the estimated distances. If an imminent accident is expected, it gives an alert to the worker with vibration and noise. Then, the PPU stores the information about the near-accident event, including the time, location, and equipment (Red dash lines in Fig. 1). The information generated by PPUs is sent to a cloud server through WiFi or 4G/5G cell networks so that a safety manager can remotely monitor the time and location of the event and statistical summary of the daily events (black solid lines in Fig. 1). Moreover, the manager can adjust system configurations and parameters in the server, and the changed configurations and parameters are sent to EPUs and PPUs so that they can be reflected on a real-time basis. Whenever a nearby PPU expects an imminent accident, the EPU also gives an alert to the equipment operator with vibration, noise, and direction. The PPUs and EPUs were designed to run for 10–12 h to remain active for daily work on a construction site. Fig. 2 illustrates the information flow framework for signal processing and alerting

Table 1. The summary of the literature review

Reference	Type of sensor	Type of alert	Advantage	Disadvantage	Case study in jobsites
Pradhananga and Teizer (2013)	GPS	Visual and auditory	Wide outdoor area coverage, No line-of-sight issue	Only for outdoor, Signal interfered by surroundings, Low accuracy	Y
Wang and Razavi (2016)	GPS-aided IMU	Visual, auditory and vibratory	More accurate, Identify speed of equipment	Only for outdoor, Signal interfered by surroundings	N
Kim et al. (2019, 2017b) and Zhang et al. (2020)	Vision	Visual and auditory	Low-cost, Identify position, speed, and category	Line-of-sight issue, Inaccurate in low or changing lighting conditions	Y
Cho et al. (2010) and Maalek and Sadeghpour (2016)	UWB	—	Applicable for both outdoor and indoor sites, Low power	Require install multiple receivers, Sensitive to metal and line-of-sight view	N
Fang et al. (2016), Lee et al. (2012), and Park et al. (2016b)	RFID	Visual and auditory	Get distance by only tracking the signal intensity of tags, Little impact on the occlusion and illumination	Require install multiple readers, Limited detection range change, Low accuracy of data, Multipath signal transmission, and Metal interference	Y (Controlled)
Park et al. (2016b, 2017a) and Park and Cho (2017)	BLE on smartphone	Visual and auditory	Low-cost, easy to calibrate, Easy to change detection ranges	Smartphone: limited function development and utilization options, High battery consumption	Y (Controlled)
Kanan et al. (2018)	Ultrasonic	Auditory and vibratory	Compact size, Low price, Lightweight, and function for daytime and night	Limited detection range, Low accuracy of data, Inconsistent detection, Small coverage area	N
Park et al. (2016b)	Magnetic field	Auditory	Varied proximity detection range	Limited detection range change, Inaccurate near metal or motors	Y (Controlled)

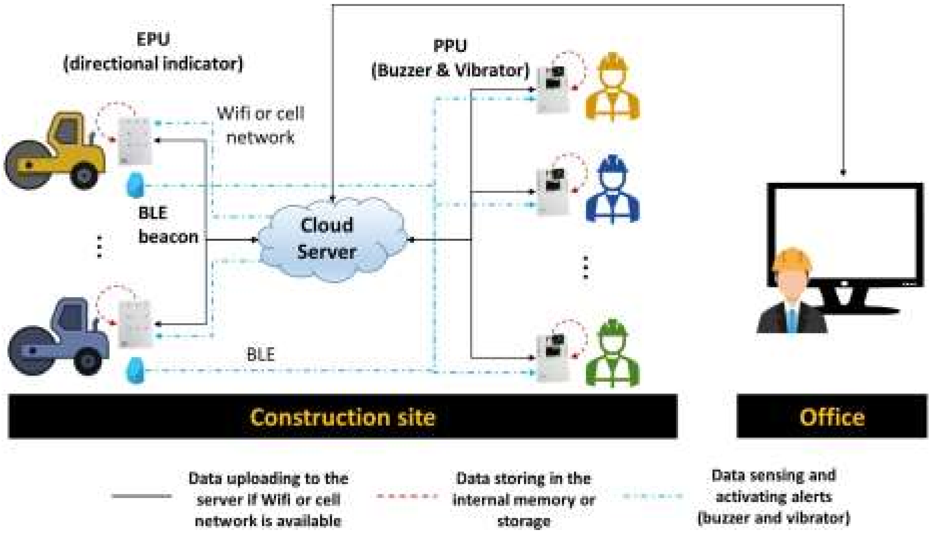

Fig. 1. Overall architecture of the proximity warning system.

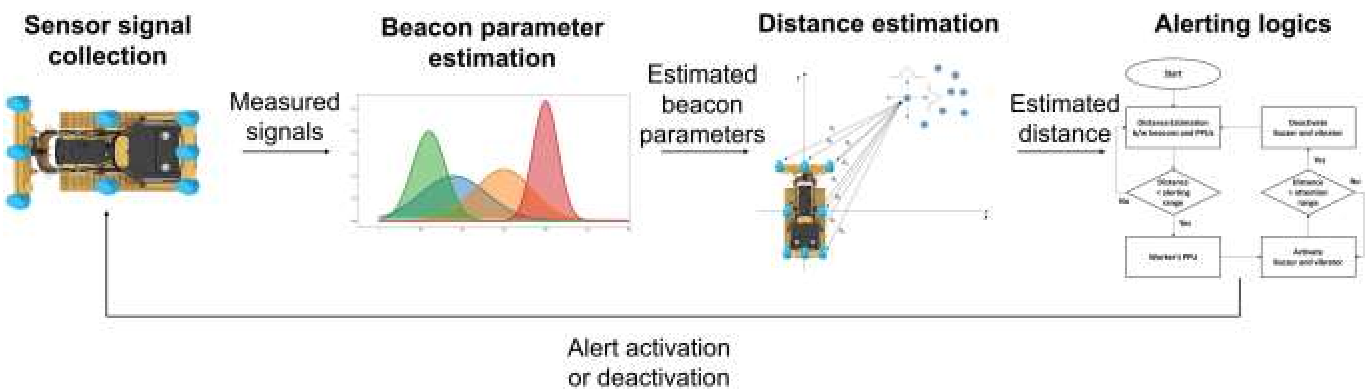

Fig. 2. Information flow framework for signal processing and alerting logic.

logic. The framework consists of sensor signal collection, beacon parameter estimation, distance estimation, and utilization of alerting logic. Once the sensor signals are collected from every beacon nearby in the server, the beacon parameters are estimated to minimize the noise in the signals. The estimated parameters are utilized to estimate the distances between the beacons and PPUs. Subsequently, the distances are used as criteria for the alerting logic of the system. Based on the logic, the system decides whether the alerting module is activated or not.

Beacon Parameters Estimation

BLE beacons, which are small-sized signal transmitters with low power consumption, are adopted in the proximity warning system. As it offers an easy-to-deploy, efficient, and inexpensive way to set up, it is an ideal tool for proximity detection and localization in a construction site where limited wireless communication infrastructure is configured. A PPU is able to measure the received signal strength indication (RSSI) values from multiple BLE beacons and estimates the distance to the beacons. The characteristics of RSSI values can be determined based on beacon parameters including the path loss exponent and the RSSI value at a 1 m distance from the beacon. A common signal propagation model to describe the relationship between RSSI and distance is as shown in Eq. (1)

$$\mathrm{RSSI} = -(10 \times N)\log_{10} d + T \quad (1)$$

where N = path loss exponent; d = distance to the beacon; and T = RSSI value at 1 m distance from the beacon.

However, the beacon parameters N and T change over time as their batteries are discharged, and thus all beacons have slightly different parameters. In order to accurately estimate the parameters of each beacon, the beacons are attached to equipment, and RSSI values are measured before they are deployed. The RSSI values are collected with PPUs in different positions, distances, and orientations.

The measured RSSI values are then used to estimate the beacon parameters. As RSSI measurements have a considerable amount of noise, a maximum likelihood estimator is adopted to handle the noise and probabilistically estimate the parameters. Using the Gaussian distribution model (Haeberlen et al. 2004), the likelihood function of RSSI measurements is defined as in Eq. (2)

$$L(N_1, T_1, \ldots, N_n, T_n; \sigma; m) = \prod_i \prod_j \prod_k \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(m_{i,j,k} - \mathrm{RSSI}(d_{i,j}; N_j; T_j))^2}{2\sigma^2}} \quad (2)$$

where n = number of beacons; $m_{i,j,k}$ = k-th RSSI measurement of the j-th beacon at the i-th measurement location;

$RSSI(d_{i,j}; N_j, T_j)$ = expected RSSI measurement of the j-th beacon at the i-th measurement location with parameters N_j, T_j.

The estimated parameters are sent to a cloud server, and the parameters are distributed to PPUs deployed on the construction site. Then, the PPUs update their distance estimation process with the distributed beacon parameters. The parameter update process is executed automatically and seamlessly so that the predeployed PPUs do not need to be manually updated.

Distance Estimation

As RSSI measurement is a noisy process, the distance estimated from the RSSI value has a noise, even though the parameters are accurately estimated. In order to filter out the noise in the RSSI measurements, three types of filtering algorithms are adopted: mean filter, extended Kalman filter, and particle filter. The filtering algorithms are applied to the RSSI values that are collected by a PPU to estimate the distance between the PPU and equipment.

The mean filter is a filtering algorithm that calculates the average of the recent signals collected for a time period. As the noise in the RSSI measurements is modeled to follow the Gaussian distribution, the mean value is able to effectively filter out the noise of the measurement process. However, since RSSI measurements may contain a considerable noise, a trimmed mean is used to remove a small percentage of the largest and smallest values.

While the mean filter estimates the distance to each beacon, the extended Kalman filter used in this study is designed to directly estimate the distance to each beacon using the RSSI measurements. The extended Kalman filter is used independently to estimate the distance to each beacon, and the estimated distances are used to estimate the distance between a worker and equipment.

The particle filter is also adopted for a similar purpose to the extended Kalman filter, but to avoid linearization and use a non-Gaussian noise model for higher accuracy and resiliency to noises. The particle filter algorithm is a filtering algorithm that estimates the internal states when partial noisy observations are given. The particle filter is implemented to estimate the relative location of a PPU to each piece of equipment by using the RSSI measurements of the beacons attached to the equipment, as shown in Algorithm 1. It estimates the relative location of a PPU in a 2D space where the equipment is centered at the origin with multiple particles that represent possible locations and updates the particles to maximize the likelihood of the particles.

Algorithm 1. Distance estimation algorithm using a particle filter developed by the authors

Variables
- P: set of particles p_m
- M: number of particles in P
- w_m: importance weight of a particle p_m

Estimate distance
1. $P = \emptyset$
2. initialize_particle(P)
3. for $i = 1$ to N do
4. observe RSSI values z_t for Δt
5. for $m = 1$ to M do
6. $p_m = p_m + N(0, \Sigma)$
7. $w_m = p(z_t | p_m)$
8. endfor
9. $\{w_m\}_{m=1}^{M} = normalize(\{w_m\}_{m=1}^{M})$
10. $P = resample(\{p_m\}_{m=1}^{M}, \{w_m\}_{m=1}^{M})$
11. endfor
12. Return estimated distance

The distance estimation algorithm using a particle filter starts with randomly distributed candidates. The importance weights of the candidates are evaluated using the likelihood function defined in Eq. (3)

$$L(p; m) = \prod_j \prod_k \frac{1}{\sqrt{2\pi}\hat{\sigma}} e^{-\frac{(m_{j,k} - RSSI(d_{p,j}; \hat{N}_j, \hat{T}_j))^2}{2\hat{\sigma}^2}} \quad (3)$$

where p = candidate's location (x, y); $m_{j,k}$ = k-th RSSI measurement of the j-th beacon; and $RSSI(d_{p,j}; \hat{N}_j, \hat{T}_j)$ = expected RSSI measurement of the j-th beacon at p with parameters $\hat{N}_j$, $\hat{T}_j$. Fig. 3 illustrates the particles used in estimating the location of PPUs.

After evaluating the importance weights of the particles, particles are resampled using the weights as the resampling probability. In order to take the worker's movement and equipment's movement into account, the position of a PPU is modeled as a free-rolling ball on a flat surface with random external force, and a certain amount of random disturbance is added to the particles. Iteratively repeating the process, the particles represent the posterior distribution of the PPU's location in the 2D space and are used to estimate the PPU's location.

However, due to the numerical instability, the likelihood function can easily converge to zero or diverge to infinity. To handle the numerical instability, the log-likelihood in Eq. (4) is used to evaluate the importance weights

$$\ln L(p; m) = -\frac{1}{2}\sum_j \sum_k \ln(2\pi\hat{\sigma}^2) - \frac{1}{2\hat{\sigma}^2}\sum_j \sum_k (m_{j,k} - RSSI(d_{p,j}; \hat{N}_j, \hat{T}_j))^2 \quad (4)$$

The log-likelihoods are normalized by adding a constant C that makes the maximum log-likelihood 1 and converted to $e^C L(p; m)$, which is used as the importance weights of the particles.

The estimation accuracy increases as the number of particles increases, but the resource requirements such as computation time, memory space, and power consumption also increase, thus significantly reducing the running time of PPUs. In order to have a

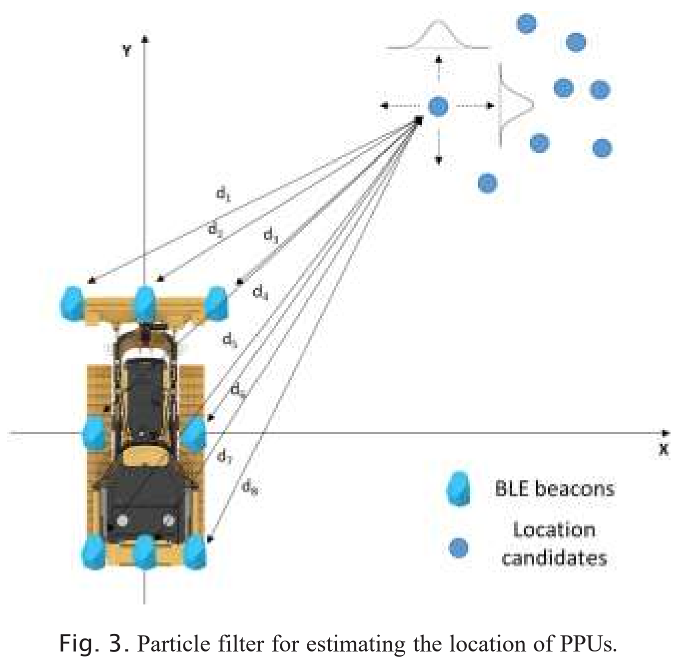

Fig. 3. Particle filter for estimating the location of PPUs.

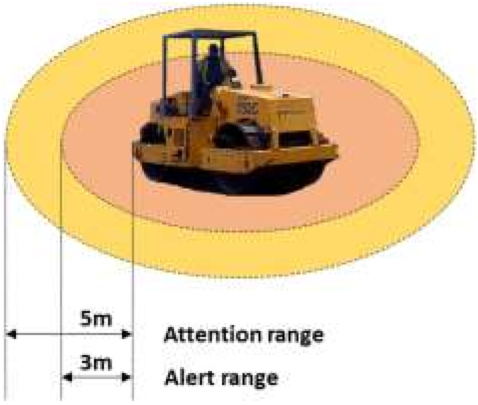

Fig. 4. Alert range and attention range of the proposed system.

balance between estimation accuracy and PPU's running time, PPUs use internal particle filters with a small number of particles when they are out of the communication range. Suppose PPUs can communicate with the cloud server using a cellular network. In that case, PPUs cooperate with the cloud server to run the particle filter with a large number of particles by offloading the heavy computation for the particle update process to the server and receiving the estimated distance from the server.

Alerting Logic

The system defines two ranges: an alert range and an attention range, as shown in Fig. 4. The alert range is determined as 3 meters for highway construction, which is the heuristically estimated distance based on the feedback from roadway paving or maintenance construction workers through a survey and interviews. Similarly, the attention range is determined as 5 meters in which workers need to pay attention to moving objects nearby. Based on the defined ranges, the system provides an alert once a worker carrying PPU enters the alert range and keeps alerting intermittently until the worker moves out of the attention range. Fig. 5 describes the alerting logic of the proposed system. While the activating criteria use the alert range for prompt and intuitive reactions of the workers, the stopping criteria use the attention range for their confidence in safety. This logic is defined to allow the worker to continuously recognize the potential hazards unless the worker escapes the hazardous area.

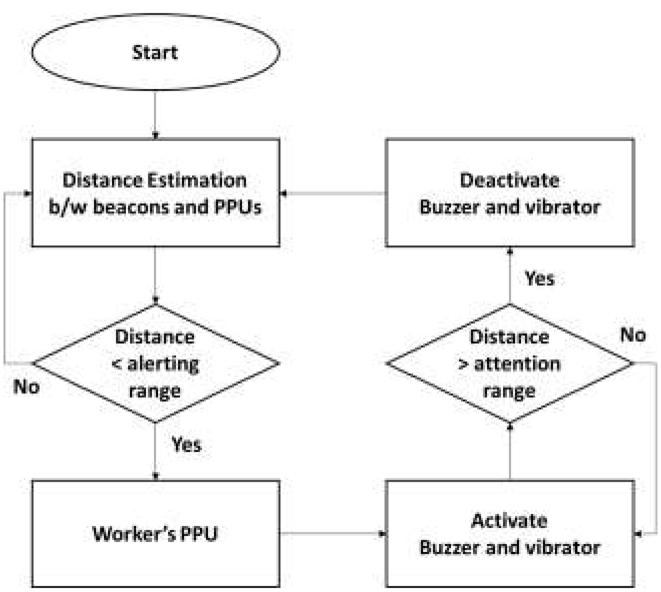

Fig. 5. Alerting logic of the proposed system.

As long as repeating alerts may not alert the workers but only disturb them, causing stress and distractions, alert suppression has been added to the alerting criteria. If a worker remains in the alert range after receiving an alert, the system assumes that the worker is operating the equipment or doing a task in close proximity to the equipment and suppresses alerts.

IoT Platform Framework

The IoT is defined as the network of physical objects supported by embedded technology for data communication and sensors to interact with both internal and external states of the objects and the environment (Haghi et al. 2017). The IoT technology has been widely utilized, enabling interconnection between objects and computing devices beyond a simple connection to the internet in various industries. In the construction industry, IoT technology can provide a reliable framework for interconnecting various entities in construction projects and computing devices and a cloud computing platform for seamless interactions (Awolusi et al. 2019). The structural condition of scaffolds was monitored by connecting strain sensors to the finite element model (Cho et al. 2018). By analyzing strain data, structural stability was automatically calculated and monitored. Construction workers' safety monitoring framework was developed based on an IoT-based real-time object tracking by integrating an accurate localization algorithm with a cloud-enabled BIM (Park et al. 2016a; Park and Cho 2017). IoT-enabled proximity alerting system was developed by deploying directional ultrasonic sensors (Kanan et al. 2018). These efforts established seamless data communication framework by utilizing IoT technology and developed the sensing and monitoring functions upon it. Hence, the concept of IoT was deployed in this study so that the information about proximity between multiple entities can be robustly transferred, stored, and processed in a cloud server and also visualized in a user interface on a real-time basis.

The BLE beacons, EPUs, PPUs, and the cloud server are closely interconnected for their own purposes. Each BLE beacon attached to the equipment is registered to the cloud server with the identification number and corresponding equipment. The EPUs and PPUs upload the incident data to the server whenever there is available WiFi or a cell network. If there is no available internet connection, PPUs store the data in the internal memory and storage so that no data are lost, and they keep preparing for the next connection. The PPUs continuously scan and detect signals from BLE beacons around them to estimate the distances from the beacons. Once the PPU is in the alert range, it activates a buzzer and a vibrator and sends incident information, including timestamp, RSSI value, the closest beacon's ID, worker ID, and equipment ID, to the server. In the EPUs, the buzzer and vibrator are activated simultaneously as well. This data communication is processed independently so that multiple objects can also be seamlessly connected without information loss.

Web-Based User Interface

The incident data sent from EPUs and PPUs are visualized through a web user interface as shown in Fig. 6. Once the data are sent to the server, it is stored in the database. Then, the essential information about the incidents is visualized through different pages. The dashboard shows the incident statistics of the current and historical data

Fig. 6. Web user interface; dashboard and worker statistics pages.

and the daily incident tendency. In addition to the dashboard, the user interface provides a jobsite layout, worker statistics, equipment statistics, and device status. The worker and equipment statistics include the identification number, occupation, work description, and the number of accumulated incidents of each worker. By integrating with the proposed IoT platform, the project manager can understand and manage the safety condition of jobsites on a real-time basis remotely.

Field Tests and Performance Evaluation

This study conducted five field tests, including a preliminary test and four evaluation tests on the Georgia Department of Transportation's construction or maintenance projects and McDermott's LNG plant construction project. The preliminary test was conducted prior to the four full evaluation tests to establish the logistics of onsite system implementation and obtain initial measurement data.

The performance of the system was evaluated in quantitative and qualitative manners. For the quantitative evaluation, this study utilized an F1-score as the evaluation metric, which is derived from three elements of a confusion matrix: true positives, false positives, and false negatives. The F1-score was calculated from the classification result by using Eqs. (5)–(7)

$$\mathrm{F1} = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{5}$$

$$\mathrm{Precision} = \frac{True\ \ positives}{True\ positives + False\ positives} \tag{6}$$

$$\mathrm{Recall} = \frac{True\ positives}{True\ positives + False\ negatives} \tag{7}$$

The classification was conducted by comparing the incident logs and recorded videos that are the ground truth of the incidents. This classification categorizes each incident into four cases such as true positive, false positive, false negative, and true negative. Here, the true positives mean incident cases where a worker is in the alerting range and the alarm goes off. The false positives mean incident cases where a worker is out of the alerting range, but the alarm goes off. The false negatives mean incident cases where a worker is in the alerting range, but the alarm does not go off. The true negatives are not considered in this study because the case is a safe situation that does not require an alert. In addition to the quantitative evaluation, the questionnaire survey was conducted with the workers who participated after each test to collect their opinions about the overall system performance.

Preliminary Test

The preliminary test was conducted to better understand the real-world onsite environment, technical needs, and required resources before the evaluation tests were conducted. A testbed of this test was a parking lot pavement site located in Georgia, as shown in Fig. 7. The given work was paving the parking lot surface, which had remaining tasks including placing and compacting the asphalt. Four types of equipment such as a roller, backhoe, dump truck, and asphalt paver were utilized at the site. Among the equipment, three pieces of equipment, including a roller, backhoe, and asphalt paver, were selected for the test. Dump trucks were excluded from the test because of their long asphalt delivery cycle time. The sensors were installed on the equipment in advance, as shown in Fig. 8. Nine ground workers participated in the preliminary test. PPUs and EPUs were distributed at the beginning of the work, as shown in Fig. 9. The participating workers wore the PPU-embedded safety vests with an identification number on the back and were asked to perform their given tasks as usual. Multiple video cameras were utilized to record the movements of the workers and equipment, and the video data were used as ground truth. During the tests, incident logs with the workers' and equipment IDs were automatically stored in the server whenever each worker was in an alerting range.

The tested system performance results are shown in Table 2. In this preliminary field test, the system's technical viability was mainly tested, and the developed signal processing and filtering methods were not used to compare the test with the later tests; thus, the test results do not show the desired system performance.

First Evaluation Test

Based on the lessons learned from the preliminary test, the first evaluation test was prepared and conducted at a road maintenance site located in Georgia. The given work was the asphalt pavement of the existing road, as shown in Fig. 10. Two pieces of equipment, such as a roller and skid steer, were utilized in the test. An asphalt

Fig. 7. Jobsite scene of the preliminary test.

Fig. 8. Sensor installation.

paver was excluded from the test because they move very slowly, and workers are supposed to work close to the paver, causing nuisance alerts. During the two-day test, six workers participated in the test each day.

As a result, the system showed a precision of 87.39%, recall of 95.10%, and F1-score of 0.911, as shown in Table 3. In this test, the improved performance was achieved because; (1) target equipment was properly selected, which is fit for the purpose of the system; and (2) an improved signal processing technique, i.e., a mean filter, was applied to find the optimal parameters of the sensors. These measures allowed the sensors' signal estimation to be more robust within a designed range so that the system could calculate the distance between equipment and workers more accurately.

Second Evaluation Test

The second evaluation was conducted at another road maintenance site located in Georgia. Two pieces of equipment, including a roller and skid steer, were utilized in the test, and four workers participated in the test. The given work was the road pavement of the

(a) (b)

Fig. 9. (a) Placing a PPU to a worker's safety vest; and (b) EPU mounted on the equipment.

Table 2. Classification and evaluation results of the preliminary test

True positive	False positive	False negative	Precision	Recall	F1-score
183	103	24	63.99%	88.41%	0.742

Fig. 10. Jobsite scene of the first evaluation test.

Table 3. Classification and evaluation results of the first evaluation test

True positive	False positive	False negative	Precision	Recall	F1-score
194	28	10	87.39%	95.10%	0.911

existing road as same as the one of the first evaluation tests. Fig. 11 illustrates the jobsite scene of the second evaluation test. In this test, three different filtering techniques, such as a mean filter, Kalman filter, and particle filter, were tested to find the optimal method for signal processing.

As a result, the system showed F1-scores of 0.835, 0.875, and 0.897 with a mean filter, Kalman filter, and a particle filter, as shown in Tables 4–6, respectively. Among three cases, the system with a particle filter showed the highest precision and F1-score and also included fewer false-negative cases. The number of false-negative cases is very important for evaluating the proximity safety sensing and alerting system because the false-negative cases are where the system did not alarm while the workers were in a dangerous situation. Hence, to improve the precision and F1-score and reduce the number of false-negative cases, a particle filter method was selected as a signal processing technique for the system.

Fig. 11. Jobsite scene of the second evaluation test.

Table 4. Classification and evaluation results of the second evaluation test with a mean filter

True positive	False positive	False negative	Precision	Recall	F1-score
86	30	4	74.14%	95.55%	0.835

Table 5. Classification and evaluation results of the second evaluation test with a Kalman filter

True positive	False positive	False negative	Precision	Recall	F1-score
70	18	2	79.55%	97.22%	0.875

Table 6. Classification and evaluation results of the second evaluation test with a particle filter

True positive	False positive	False negative	Precision	Recall	F1-score
65	14	2	83.33%	97.10%	0.897

Third Evaluation Test

The third evaluation was conducted at another road maintenance site located in the state of Georgia. The test condition was the same as the second evaluation test; a roller, a skid steer, and four workers were involved in the road pavement work, as shown in Fig. 12. As a result, an F1-score of 0.883 was achieved in Table 7. Only the particle filtering algorithm was applied to this test based on the finding from the 2nd evaluation test.

Fourth Evaluation Test

The fourth evaluation was conducted in an LNG plant construction site located in the state of Texas. The given work was moving temporary facilities, e.g., job trailers, barricades, and temporary restrooms, as shown in Fig. 13. Two pieces of equipment, such as a dozer and skid steer, were utilized in the test. Six workers participated in the test. As a result, the system showed the highest F1-score, which is 0.931 as shown in Table 8. Table 9 shows the summary of all tests, including a preliminary test and four evaluation tests.

Qualitative Evaluation

The questionnaire survey was conducted with the workers after each test to collect their opinions about the performance of the system. The survey included questions about the noticeability of the alerts, effectiveness of the system, and preferred alerting range. The results from the survey with 23 responses are shown in Fig. 14 and Table 10.

As a result of the survey, 91% of the workers were able to recognize the alerts on the jobsites properly. The combination of auditory and vibratory alerts was effective since most workers could recognize at least one of them in noisy working environments.

Discussion

From a series of field tests with real construction projects, the system showed performance improvement. Among the evaluation metrics, recall is considered the top priority because false-negative cases are the most critical case associated with safety. As the false-negative cases indicate that the system failed to detect the dangerous situation despite its presence, reducing the number of false negatives is important to improve not only the technical performance but also the practical safety performance. As a result of the repeated tests with continuous sensor calibrations and sensor signal filtering techniques, a recall of 97.45% was achieved from the fourth evaluation test. The sensor signals from the BLE beacons inherently include noise. Without the calibration and signal processing technique, the signals are not reliable enough to

Fig. 12. Jobsite scene of the third evaluation test.

Table 7. Classification and evaluation results of the third evaluation test with a particle filter

True positive	False positive	False negative	Precision	Recall	F1-score
98	21	5	82.35%	95.15%	0.883

Fig. 13. Jobsite scene of the fourth evaluation test.

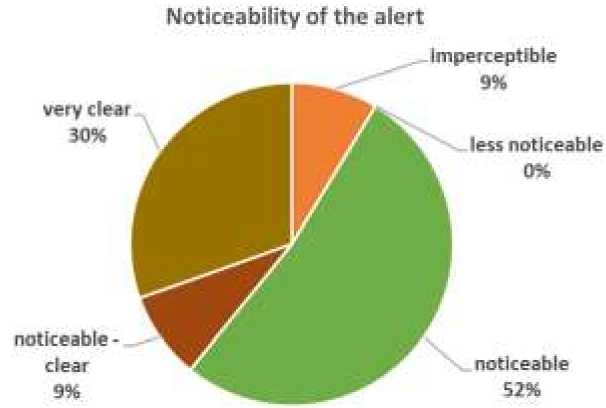

Fig. 14. Results of the question about the noticeability of the alert.

estimate the distance. This phenomenon was also observed in the preliminary test. In the preliminary test, the precision, recall, and F1-score were relatively low because the proper calibration and advanced signal processing techniques were not involved. However, once they were deployed based on the knowledge accumulated from the repeated tests, the system showed higher performance scores in the later test. Meanwhile, some workers answered that the system provided alerts when they were out of range occasionally. This phenomenon is because of false-positive cases. In these cases, the system may underestimate the distances between workers and equipment when they do not fully escape the attention range or work around the boundary. This can cause nuisance alerts, which may be annoying and make them less sensitive to the alerts. Based on the analysis and survey results, it is found that a logic to filter out the false-positive cases is needed to further improve the performance of the system. For example, a rule-based time restraint logic can be added to suspend the continuous alerts if a worker performs a task near heavy equipment for a long time.

From the worker's perspective, the system showed that the provided auditory and vibration alerts were clearly recognized in time. Although the PPUs were closely attached to the worker's ears, there might be a possibility that a worker did not recognize the alert in a noisy and congested jobsite. However, the questionnaire survey result showed that 91% of workers were able to recognize the alert properly. It was possible because two different types of alerts were provided simultaneously so that the worker could recognize either auditory or vibration alerts even if the worker did not recognize one of them. In addition, the workers positively answered the question about the effectiveness of the system. This showed that both operators and workers were able to better recognize the proximity hazards by using the system.

Table 10. Results of the question about the effectiveness of the system

Effectiveness of the system		
Answers	Counts	Percentage
0 (Not effective at all)	0	0%
1	1	4.35%
2	0	0%
3	2	8.70%
4	0	0%
5	3	13.04%
6	4	17.39%
7	5	21.74%
8	1	4.35%
9	2	8.70%
10 (completely effective)	5	21.74%
Average	6.83	N/A
Total	23	100%

There are several lessons learned from a series of case studies for practical implementation as follows:

- The target equipment should be thoroughly selected based on the nature of its movement, given tasks, and safety statistics. Slowly moving heavy equipment, e.g., asphalt paver, does not need proximity alerts.

Table 8. Classification and evaluation results of the fourth evaluation test with a particle filter

True positive	False positive	False negative	Precision	Recall	F1-score
306	37	8	89.21%	97.45%	0.931

Table 9. Summary of the preliminary test and four evaluation tests

Test	Tasks	# of workers	Equip.	Filtering methods	Precision	Recall	F1-score
Pre-test	Parking lot pavement	9	Roller, Backhoe, Asphalt paver	N/A	63.99%	88.41%	0.742
1st test	Road pavement	12	Roller, Skid steer	Mean filter	87.39%	95.10%	0.911
2nd test	Road pavement	4	Roller, Skid steer	Mean filter	83.33%	97.10%	0.897
				Kalman filter	83.33%	97.10%	0.897
				Particle filter	83.33%	97.10%	0.897
3rd test	Road pavement	4	Roller, Skid steer	Particle filter	82.35%	95.15%	0.883
4th test	Temporary facility re-install	6	Dozer, Skid steer	Particle filter	89.21%	97.45%	0.931

- The sensor calibration for each piece of equipment should be preceded before the system implementation to achieve the expected performance. The calibration should be done while an engine is running to consider any electromagnetic fields generated by the engine. The electromagnetic field can change RSSI values directly or generate noises so that the distance estimation error can be caused. Thus, those factors that may interfere with the BLE signals should be identified and calibrated before implementing the system. The calibration process takes up to 20 min for a piece of equipment.
- The wireless communication latency may exist depending on a network's condition or the location of BLE sensors, which can also affect the system's performance. Hence, it should be examined during the calibration process. A round-trip time of a test alert from a PPU to an EPU through the cloud server can be measured as the latency, and it should be confirmed that the latency is small enough to alert the workers and equipment operators. In the tests conducted in this study, it was found that the round-trip communication between a PPU and EPU through the server took up to 300 ms depending on the router setting. This latency examination process takes up to 3 min.
- In hot weather, the heat generated from the PPUs should be continuously monitored to prevent damage to devices.
- When the BLE beacons are not used, their power configurations should be changed to low-power modes to reduce power waste.

Conclusion

This study proposes a proximity warning system that provides an alert to workers whenever they are close to heavy equipment by using BLE sensors. Also, four full-scale case studies were conducted on real construction sites to practically validate the system. Through continuous improvement in the performance with the repeated tests, the system showed a precision, recall, and F1-score of 89.21%. 97.45%, and 0.931, respectively. The proposed system did not interrupt any usual working conditions and workers' working routines. The users' experiences were investigated through the questionnaire survey in terms of the recognizability of the alert and the effectiveness of the system. It showed that 91% of the workers were able to recognize the alert properly in time, and the workers positively answered the question about the effectiveness, which was 6.83 points out of 10 points. With these findings, this study can provide a practical solution to proximity hazards in dynamic and congested construction sites by enhancing the workers' abilities to recognize the struck-by hazards.

The main contribution of this study is two folds. First, this study thoroughly investigated the technical and practical feasibility of the proximity warning system in real construction sites. This study explored performance improvement and learned practical lessons to implement the system on an actual jobsite. Second, this study validated the system without any restricted or controlled settings and environments that can affect the system's performance. Unlike a lab or controlled environment, real-world construction sites are unpredictable, continuously change, and involve numerous entities such as workers and equipment. The proposed system requires the workers to wear only a safety vest with an embedded safety alert device (PPU), which is a noninvasive approach, to perform the given ordinary tasks. Hence, it is expected that this proposed system can practically improve the safety conditions in dynamic construction sites.

Future research will be conducted to address several limitations of the proposed system. First, the automated BLE beacon characterization and calibration methods will be developed to easily deploy the system in a new jobsite with minimum manual effort. This will also help implement the system in large-scale and congested construction sites and further examine its practical and technical feasibility in different types of construction projects. Second, the functions of EPUs rely on WiFi or cell network availability. If such networks are not available, only PPUs work properly. However, the research team has been resolving this issue with an improved communication structure in which PPUs and EPUs can provide alerts regardless of the availability of WiFi or a cell network and store the data internally until WiFi or a cell network is available. Thus, the future system will not be affected by the availability of WiFi or cell network. Third, an in-depth questionnaire survey and interview with a thorough analysis will be conducted to investigate the impact of how different hardware configurations of PPUs, e.g., PPU placement, PPU weight, and recognizability under harsher conditions, affect the performance of the system and the user's experience. Last, the technology trust of workers will be investigated by collaborating with relevant experts to further examine the usability of the system in real-world projects. With these directions, the proposed system can be further improved as a jobsite proximity hazard management solution.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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