

Risk-Incorporated Trajectory Prediction to Prevent Contact Collisions on Construction Sites

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Abstract: Many construction projects involve a plethora of safety-related problems that can cause loss of productivity, diminished revenue, time overruns, and legal challenges. Incorporating data collection and analytics methods can help overcome the root causes of many such problems. However, in a dynamic construction workplace collecting data from a large number of resources is not a trivial task and can be costly, while many contractors lack the motivation to incorporate technology in their activities. In this research, an Android-based mobile application, Preemptive Construction Site Safety (PCS2) is developed and tested for real-time location tracking, trajectory prediction, and prevention of potential collisions between workers and site hazards. PCS2 uses ubiquitous mobile technology (smartphones) for positional data collection, and a robust trajectory prediction technique that couples hidden Markov model (HMM) with risk-taking behavior modeling. The effectiveness of PCS2 is evaluated in field experiments where impending collisions are predicted and safety alerts are generated with enough lead time for the user. With further improvement in interface design and underlying mathematical models, PCS2 will have practical benefits in large scale multi-agent construction worksites by significantly reducing the likelihood of proximity-related accidents between workers and equipment.

Keywords: Construction safety; trajectory prediction; real-time tracking; GPS; Markov model; risk attitude; mobile application.

I. INTRODUCTION

Unlike manufacturing facilities or assembly lines almost no construction project occurs in a stationary work setting, since large number of resources constantly move and frequently interact with one another in an unstructured and transient manner. As a result, addressing safety issues in construction is rarely trivial and involves more challenging problems than other industries. Despite extensive research and the practice of strict enforcement of regulatory systems and standards related to occupational safety and health, construction still remains one of the most hazardous occupations worldwide. In this paper, a framework for real-time preemptive site safety is laid out that can enhance jobsite safety conditions through proactively using the vast amount of site data captured and processed continuously by ubiquitous data collection devices. Collected data, if properly used, can provide valuable insights into spatiotemporal interactions between construction resources, which can in turn significantly enhance our understanding of and ability to predict similar future events, and ultimately alert individuals to avoid hazardous incidents. The use of such modern pervasive data sensing and mining methods can therefore ensure a universal and timely deployment of effective safety practices on the jobsite.

Previous research has cited limited work space, and frequent interactions between workers, equipment, and tools as the leading factors in many injuries and casualties in the workplace [1]. Specifically, the diverse and complex nature of most construction tasks often brings

workers and equipment to close proximity of one another which can increase the likelihood of life-threatening contact collisions. Arguably, the most hazardous encounters occur when two or more construction resources move too close to each other while overlooking potential safety risks. A real-time proactive safety warning approach is thus necessary to track the location of construction resources and generate safety alerts before they get too close to each other. To address this issue, a scalable safety framework is presented in this study, that fuses spatiotemporal data of workers and site hazards with quantifiable measures of an individual's behavior to generate proximity-based preemptive safety alerts in real time. A mobile application, Preemptive Construction Site Safety (PCS2), is developed and tested to validate the designed methodology. This paper also presents a high-level review of related literature in construction safety, existing practices, resource tracking, trajectory prediction, and risk behavior.

II. LITERATURE REVIEW

A. Injury Statistics in the Construction Industry

Inherent to the construction industry are high accident rates and hazardous activities that have resulted the industry to rank as one of the most dangerous industry worldwide [2]. In the U.S. alone, more than 17% of all work-related deaths are related to construction [3]. According to the Bureau of Labor Statistics (BLS), approximately 925 fatal injuries happened in 2015 in the

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construction industry, and approximately \$15 billion of revenue is lost each year due to construction injuries and fatalities [4]. BLS also reported that there were approximately 200 thousand nonfatal workplace injuries and illnesses in the construction sector in 2015, an equivalent of 3.4 cases per 100 full-time workers. Since its establishment in 1971, the Occupational Safety and Health Administration (OSHA) has aimed at creating safe working environments by enforcing safety regulations [5]. While these regulations have resulted in an overall positive trend in workplace safety the number of injuries and accidents is still high. OSHA identifies fall, electrocution, struck by object, and caught in between as four major causes of construction injuries, named as “fatal four”. As shown in Figure I, among these four causes, fall, struck by object, and caught in between directly or indirectly relate to proximity of construction resources, and contribute to almost 51% of all construction-related fatalities.

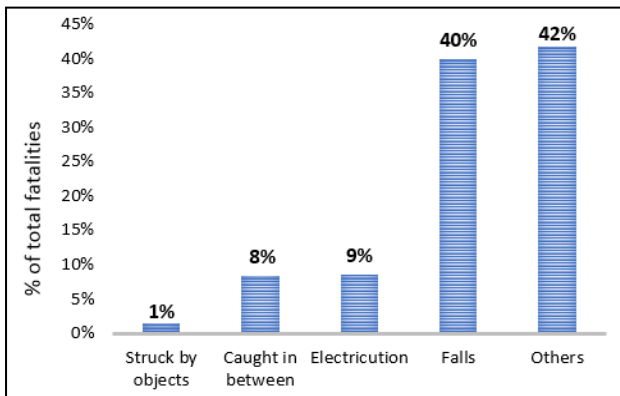


FIGURE I
FOUR PRIMARY CAUSES OF CONSTRUCTION WORKER FATALITIES

In their research, Hinze and Teizer [6] categorized injuries and fatalities caused by lack of visibility and showed that out of 659 equipment- and visibility-related fatalities, 521 cases were due to struck by moving equipment. Other factors included being hit by equipment buckets, material being dropped or lowered by equipment, electrocution when equipment contacted power lines, and rollovers when equipment were operated on a steep slope. Another issue explored in the same study was the direction of move of a piece of equipment at the time an incident occurred. Figure II portrays that out of 594 equipment-related incidents, 72.6% of cases occurred when the equipment was travelling in reverse direction while only 18.5% of cases resulted from equipment traveling forward. This study of Hinze and Teizer [6] demonstrated a strong correlation between workplace accidents and proximity to construction resources.

There is also a significant cost associated with construction injuries and fatalities. In the U.S., the total cost of fatal and non-fatal injuries in the construction industry were estimated to be \$11.5 billion in 2002 which was 15% of all injury and fatality costs in the private sector [7]. Moreover, it was estimated that in 2002, each fatal or non-fatal construction injury cost an average of

\$27,000, compared to \$15,000 in other industries [7]. Another study showed that between 2011 and 2013, the annual economic cost of construction-related fatalities was approximately \$270 million in Illinois, \$150 million in Indiana, and \$125 million in Iowa [8,9].

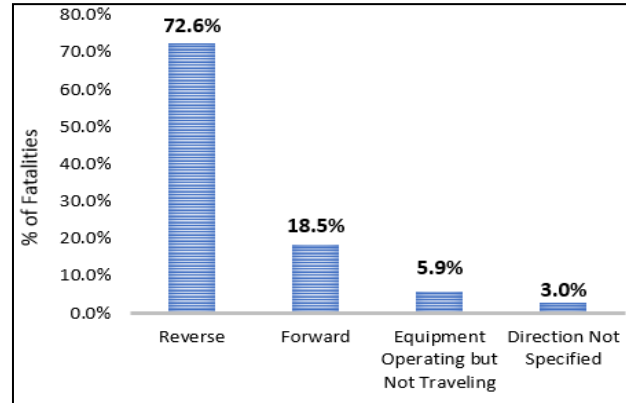


FIGURE II
EQUIPMENT MOVEMENT DIRECTION WHEN ACCIDENT OCCURS (N=594)

B. Existing Safety Practices

Existing construction safety management practices are traditionally carried out in a fragmented manner [10]. To this end, it is worth noting that quite often the main focus of construction management which is productivity improvement (i.e. lower product cost and shorter completion time) is in clear contrast with workplace safety requirements [10]. Several researchers have proposed different approaches to integrate safety in construction design, planning, and control [11]. Ideally, safety measures must be taken into consideration as early as the design phase where designers can play an important role by implementing safer designs and directing the choice of construction means and methods to avoid or reduce hazardous situations on the jobsite [10]. However, due to the unpredictable and dynamic nature of construction field activities, it is challenging for designers to foresee each and every hazardous situation before the construction process begins. Following the design phase, the next step in a project lifecycle where safety precautions must be practiced is construction. This is normally done by checking and enforcing common industry safety regulations such as those of OSHA [12]. Previous research has indicated that although complying with OSHA regulations contributes to an overall safe jobsite, such rules and regulations may not be enough to avoid all incidents involving physical contacts between objects (a.k.a. contact collisions) [13]. The main underlying reason behind this is that OSHA mainly enforces the use of passive safety devices (e.g. hard hats, safety shoes, goggles, face shields, reflective clothing, hearing protection, wet weather gear, and filter masks) also known as Personal Protective Equipment (PPE), which are not capable of providing proper warning before a collision happens. In addition to these implementation issues, the lack of education and experience in safety

management has been identified as a major cause in many incidents [14]. Typically, knowledge about safety is conveyed through textbooks, specialized training, apprenticeship programs, and job experience [15]. These safety programs deliver information about site risks, hazards, and safe behaviors. For example, OSHA offers a 30-hour voluntary outreach class for personnel with supervisory authority over workplace safety and health, aiming to educate them about standards, procedures, and policies with special emphasis on identification, avoidance, abatement, and prevention of workplace safety hazards [16]. It has been stated that existing safety training programs are often not sufficiently engaging, offered within a short period of time, and do not take advantage of active workers' participation [14]. In addition, construction accidents can happen due to errors, negligence, omissions, and misunderstandings of one or two workers, which is difficult to pinpoint in advance [17].

C. Technology in Construction Safety

During the past several years, and with the invention of more robust sensing technologies, researchers have also studied the feasibility of real time proactive proximity safety warning systems for construction workers. For instance, Teizer et al. [13] conducted an experiment using a radio frequency (RF) system which gave audio-visual alerts to workers and equipment operators when they came to close proximity to each other. Ding et al. [18] presented a safety management tool based on the Internet of Things (IoT) which integrated fiber bragg grating (FBG) sensors and radio frequency identification (RFID) for labor tracking. Another research based on location-aware technologies that combined wireless communication, global positioning system (GPS), and geographic information system (GIS) showed the potential of real time safety warning by automatically detecting hazards, alerting drivers to avoid collisions, and ultimately ensuring reliable navigation of construction equipment [19].

Not only are information and communication technologies such as building information modeling (BIM), virtual design and construction (VDC), and GIS emerging tools in architecture, engineering and construction (AEC), they can also facilitate the integration of safety measures in design, planning, and monitoring of field activities. For example, Zhang et al. [12] presented a rule-based BIM-enabled engine to automatically analyze a building model, detect fall-related safety hazards, and suggest preventive actions to the user. Hadikusumo and Rowlinson [20] created a virtual reality (VR)-based design-for-safety process database which took input from the building design phase to identify safety hazards. An integrated system for construction safety management based on 4D CAD models and a rule-based algorithm was developed by Benjaoran and Bhokha [10], which integrated safety measures at the early stages of design and planning to help all parties prepare for safety constraints before the actual work begins. Bansal (2011) developed a platform using GIS-based navigable 3D

animation, linking information from the project schedule with the safety recommendation database to predict the places and activities having higher risk potentials. Video camera and time-lapsed photography have been also used frequently to measure the overall safety conditions of construction sites and identify potential violations by workers and contractors [21].

D. Automated Construction Resource Tracking

As stated earlier, contact collisions are the major cause of construction injuries and fatalities. In order to assess and understand the underlying characteristics of this kind of incidents, obtaining context-aware information including time-stamped positional data of construction resources is critical [22]. However, despite recent developments in construction measurement and sensing technologies, collecting precise and timely location data from construction resources still remains a rather challenging task [23]. To remedy this problem, past studies have investigated methods of automatically tracking resources (personnel, equipment, materials) in construction and facilities projects. In particular, several technologies for indoor and outdoor location tracking and remote sensing have been used. For example, researchers explored the prospect of automatically measuring labor input by tracking their position [24]. Using this approach, the time each worker spent on an activity was estimated with an accuracy of 10%-20%. Sacks et al. [24] and Navon et al. [25] used GPS to track earthmoving equipment in regular intervals and convert location data into equipment productivity and material consumption. Other researchers also used GPS to track construction equipment and materials [22, 26, 27, 28, 29]. RFID is another location tracking technology used for tracking construction resources. In an early attempt, RFID was used to track high-value materials on construction jobsites [30]. Song et al. [31] used RFID to track the delivery and receipt of fabricated pipe spools. Goodrum et al. [32] developed a prototype tracking system to monitor hand tools in a mobile environment. Indoor GPS, wireless local area network (WLAN), inertial navigation system (INS), Bluetooth, infrared, and ultrasonic are some of the available technologies for indoor tracking, and several applications have been developed based on these technologies [22, 33, 34, 35,36].

As the number of mobile phone users has been steadily growing with almost 2 billion smartphone users in the market by late 2015 [37], researchers in multiple disciplines have also directed their efforts toward utilizing a host of mobile-embedded sensors (e.g. GPS, accelerometer, gyroscope, digital compass). In an early study, an Android-based indoor/outdoor localization system was developed, taking advantage of GPS and WiFi modules, to locate personnel carrying smartphones [38]. Recently, the development of GPS and location-aware applications have gone beyond simply navigating through a route or obtaining the location of the phone. For instance, GPS data collected from cellular phones were used to gather large volumes of traffic information, process the collected data, and distribute it back to the

phone users in real time for traffic analysis and monitoring [39]. Also, a smartphone-based navigation application was developed to alert visually-impaired pedestrians with an audible message at decision points prior to their arrival at a work zone [40].

The application of smartphone-based location-aware technologies in healthcare is also explored in several studies. For instance, a generic Android-based framework was developed to collect field data by epidemiologists and ecologists with the help of a web database and GPS data [41]. The potential of location-aware smartphone technologies to help the elderly and visually-disabled persons has been also described in several studies [42].

E. Analysis of Workers' Risk-Taking Behavior

Within the construction domain, extensive research has been carried out to improve the safety environment for field workers. The interface of safety and human behavior has been the subject of previous studies in other domains. For instance, Salminen [43] conducted a survey that showed young workers under the age of 25 experience a higher injury rate than older workers. Gardner and Steinberg [44] conducted an experimental study with 306 participants in three age groups – adolescents (13-16), youth (16-22), and adults (24 and older) to measure risk preference and risky decision making, and concluded that risk-taking and risky decision-making decrease with age. Cooper [45] stated that the risk-taking propensity of an individual depends on his or her perception of the situation, past experience, and personality. Gender differences in risk-taking attitude is also studied in several projects. For example, Charness and Gneezy [46] showed that women are generally more risk averse in financial issues than men. Their study demonstrated that women make smaller investments in a risky asset than men do. In addition, risk-taking propensity of men has been observed to be higher than women in other domains. For example, according to the U.S. Department of Transportation, male drivers are three times more likely to be involved in fatal car accidents. Also, it was reported that female drivers use seat belts substantially more often than men [47].

F. Motion Trajectory Prediction

Trajectory prediction is a critical component of almost all spatial collision algorithms [48]. Researchers have studied a variety of trajectory prediction techniques in several fields such as robotics [49], aerospace engineering [48], maritime traffic management [50], physics and mechanics [51], and meteorology [52]. Gong and McNally [48] presented a methodology based on statistical analysis to improve the quality of trajectory prediction for decision support applications such as conflict detection and arrival metering for air traffic management. Perera et al. [50] presented a methodology of integrating intelligent features with vessel traffic monitoring and information system (VTMIS) to predict navigational vessel trajectory using extended Kalman filter (EKF) [53]. One of the first attempts to collect global system for mobile communication (GSM) data was

made by Laasonen et al. [54] who proposed a prediction model which took a sequence of recent cell transitions to find the most probable cell the user will enter next. Ashbrook and Starner [55] used Markov model [56] to predict a user's next location from his or her significant past locations extracted from GPS data. Mathew et al. [57] designed a hybrid method to predict human mobility by training a HMM using historical location clusters. Vasquez and Fraichard [58] proposed a technique that learns the pattern of a moving object and applies a pairwise clustering algorithm to clustered trajectories to predict that object's future position. A hybrid prediction model, coupling historical trajectory patterns and an object's recent motion was also explored [59] and demonstrated accurate results than existing prediction models at that time. Monreale et al. [60] proposed a trajectory pattern tree to predict the next location of a moving object using GPS data with a certain level of accuracy. Gambs et al. [61] used the extended mobility Markov chain (MMC) theory to predict the next location of an individual using his previously visited locations. Kim et al. [52] presented a destination prediction framework which detects a user's location via k-nearest neighbour (KNN) and decision trees, and predicts his or her future destination using HMM.

III. RESEARCH METHODOLOGY

A. Trajectory Prediction Using HMM

Machine learning tools, specifically Markov chain (MC) and HMM have been previously used in context-aware applications. In HMM, trajectories are treated as discrete stochastic processes (i.e. random walks). In this research, a trajectory prediction technique based on HMM is designed to predict the future location of construction workers on the jobsite. As shown in Figure III, training trajectory data are first collected and stored in a trajectory database (DB). Next, statistical parameters are extracted from the dataset and used to train the HMM. New trajectory data is then collected from a target user (i.e. construction worker) and used as the input of the trained HMM to predict that worker's immediate future positions as he or she walks around the jobsite. Clearly, since HMM is a trainable prediction method, with time and as more trajectory data come in, the model better adapts itself to the real-world movement patterns of each construction worker and can provide more accurate predictions.

In this research, in order to train the HMM, 71 trajectories were collected. Each collected trajectory was divided into smaller (12-second long) normalized trajectory sections as shown in Figure IV and K-mean clustering was used to group all such sections into 8 clusters (a.k.a. latent segments). Statistical parameters including mean, variance, and covariance were then extracted from these clusters. Considering the limited horizon assumption, which states that the probability of a future location depends only on the current location [56], given a sequence of latent segments $S_0, S_1, S_2, \dots, S_n$ the probability of occurrence of a future latent segment S_{n+1} depends only on the current latent segment S_n , as stated in

Equation (1). These probabilities are termed transition probabilities and together create the transition matrix.

$$P(S_{n+1} / S_n, S_{n-1}, S_{n-2}, \dots, S_0) = P(S_{n+1} / S_n) \quad \text{Eq. (1)}$$

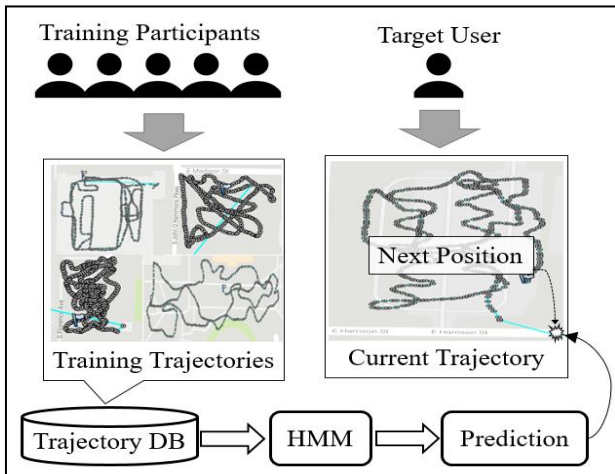


FIGURE III
MAIN STEPS OF THE DEVELOPED HMM-BASED TRAJECTORY PREDICTION METHOD

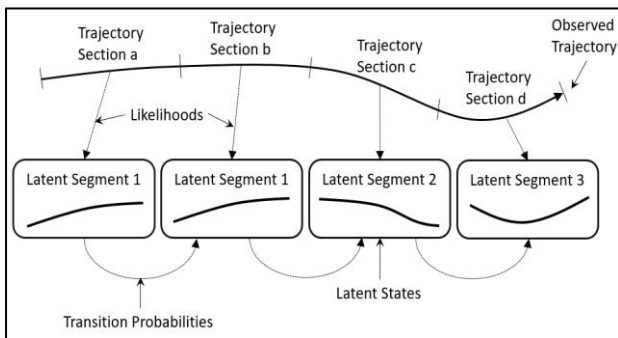


FIGURE IV
KEY ELEMENTS OF HMM PREDICTION MODEL

Next, bivariate normal probability density function was used to calculate the likelihood of each section to be generated from a specific latent segment, and all calculated probabilities were stored in a likelihood matrix. Since the sequence of sections over a latent segment is known from the training data, HMM was trained using all 71 trajectories to calculate transition probabilities between states. Given that initially trajectories have different start positions, directions, and velocities, they must be first normalized by a translation to the origin (0, 0), followed by a rotation so that the initial direction is (1, 0), and finally scaling so that the initial velocity is unit velocity. This results in a total of 4,662 normalized short trajectory sections extracted from the training data. The overall training process of the HMM is demonstrated in Figure V which involves calculating the transition probabilities between latent segments throughout all training trajectories.

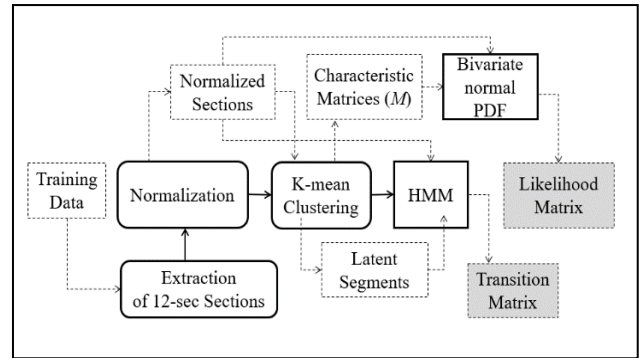


FIGURE V
INPUT-PROCESS-OUTPUT DIAGRAM OF HMM TRAINING STAGE

Transition probabilities are in fact conditional probability distribution functions (PDFs) of a specific latent segment to be followed by other latent segments. As the sequence of short trajectory sections over the eight latent segments is known from the training data, running all training trajectories through the HMM provides an 8-by-8 probability matrix containing transition probability distributions of each latent state. This process is implemented in MATLAB using `hmmestimate(seq, states)` which returns the maximum likelihood estimate of transition probabilities of the HMM for sequence `seq` and known states (latent segments) `states`. Next, the likelihood (\mathcal{L}) of normalized sections to be generated from a latent state and the PDF of the bivariate normal distribution is implemented in MATLAB as `mvnpdf(x, μ, Σ)` which returns the density of the multivariate normal distribution with mean μ and covariance Σ . The likelihood of each trajectory section to be generated from a latent segment is calculated and stored in the likelihood matrix.

Once the HMM is fully trained, the resulting transition matrix and the likelihood matrix are applied to future trajectory data to perform trajectory prediction. In a nutshell, to predict the next section of a new trajectory, the model first checks the likelihood matrix and finds the latent segment that best resembles the observed trajectory section. Next, it determines the most probable future latent segment using the transition matrix, and finally provides the most likely trajectory section from the likelihood matrix. During the prediction stage, at least 12 data points are required. As shown in Figure VI, the observed latest section (l_n), which contains 12 data points is first normalized. Next, the maximum likelihood of that section to be generated from a specific latent segment (S_n) is computed from the likelihood matrix. The latent segment with maximum likelihood is then used to compute the next most probable latent segment (S_{n+1}) from the transition matrix. Finally, the likelihood matrix is used to find the trajectory section which has the highest likelihood to be generated from that latent segment (S_{n+1}). The trajectory section is then denormalized and used as the predicted future trajectory (l_{n+1}). Since the first two points of l_{n+1} are patched to the existing trajectory, the trained HMM model can predict up to 10 seconds in advance.

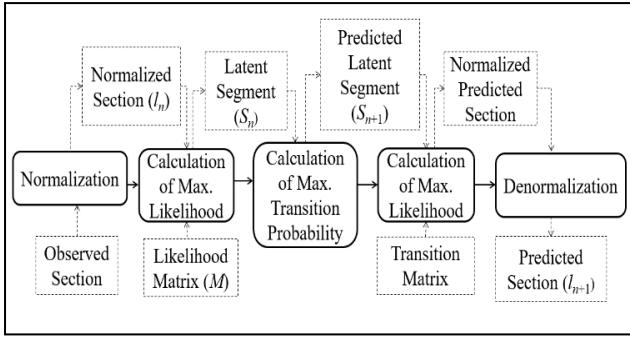


FIGURE VI

INPUT-PROCESS-OUTPUT DIAGRAM OF HMM PREDICTION STAGE

B. Incorporating Risk-Taking Behavior into Trajectory Prediction

As stated earlier, in addition to a robust motion trajectory prediction model, this research attempts to formalize a method to incorporate the risk attitude of workers with the developed HMM. It is imperative that a trajectory predicted solely based on mathematical principles must be adjusted to also reflect the extent to which a worker is inclined to take or avoid risks. In this work, the basic principle applied to incorporating risk behavior in trajectory prediction is that if a worker exhibits a risk-taking behavior, his or her predicted future position is moved closer to the hazard zone since the worker is more likely to be on a collision course. In order to make the analysis more conservative, no calibration is made for a risk-averse worker. Two types of risk factors are considered, namely the angular risk factor (α), and the linear risk factor (m). A worker's risk factor (k) at any given timestamp is then calculated by multiplying angular and linear risk factors at that timestamp. In order for this approach to yield accurate results, it is important to also properly quantify a cumulative risk attitude (a.k.a. the aggregate risk factor or μ) of each worker. To this end, a self-learning formulation is used to continuously calculate, store, and update the aggregate risk factor based on the history of a worker's movements in the vicinity of hazards.

The angular risk factor (α) is calculated based on the worker's actual trajectory. From Equation (2) and Equation (3), within a certain vicinity of the hazard, if a worker is moving directly toward the hazard center, α is 1 or 100%, which means he or she is a full risk-taker. In contrast, if a worker is moving in the opposite direction from the hazard center, α is 0, which implies that in that specific instance of time, he or she is a full risk-averse. In cases where the direction of workers' movement is at any angle (θ) with the hazard center, α is between 0 and 1.

$$\theta = \cos^{-1} \frac{a^2 + b^2 - c^2}{2ab} \quad \text{Eq. (2)}$$

$$\alpha = 1 - \frac{\theta}{180} \quad \text{Eq. (3)}$$

A hypothetical trajectory is plotted in Figure VII with a stationary hazard zone. The value of α at each position is superimposed in form of a circle on the worker's

coordinate at that point. When the worker approaches the hazard directly, the circle grows, implying that the value of α approaches 1 (maximum possible). In this scenario, it can be inferred that the worker is exhibiting a risk-taking behavior. On the other hand, as the worker is passing by the hazard, the circle shrinks indicating that α approaches 0 (minimum possible). In this case, the worker demonstrates a risk-averse attitude.

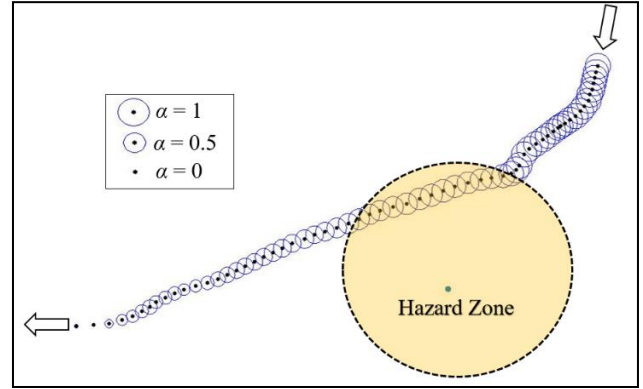


FIGURE VII

 VARIATION OF ANGULAR RISK FACTOR (α) NEAR THE HAZARD ZONE

The linear risk factor (m), on the other hand, is based on the discrepancy between predicted and actual positions. It represents the radial error of the predicted position relative to the actual position, considering the hazard zone at the center of the circle. In Figure VIII, the predicted future position, calculated by the trajectory prediction model is shown as point 4'. The linear distance (d) between the actual position (point 4) and the hazard center H , as well as the linear distance (d_1) between the predicted position (point 4') and the hazard center H are calculated using the Haversine formula. The linear risk factor (m) represents the difference between d and d_1 as calculated by Equation (4). Knowing m , the instantaneous risk factor, k can be calculated by Equation (5).

$$\text{Linear Risk Factor } (m) = d_1 - d \quad \text{Eq. (4)}$$

$$\text{Risk Factor } (k) = \alpha \times m \quad \text{Eq. (5)}$$

As previously mentioned, to yield more accurate results, it is important to properly quantify the cumulative risk attitude (a.k.a. the aggregate risk factor or μ) of each worker.

An individual's aggregate risk factor is calculated and updated based on the history of his or her movements in the vicinity of hazards. Initially, μ is set equal to zero and workers are all assumed to be neutral (neither risk-taker nor risk-averse). This will be modified over time as positional data is collected. In the next iteration, point 4' is shifted k units toward H . The adjusted position is labelled as 4''. Next, given k and d_1 , the modified linear distance d_2 (between H and 4'') is calculated and compared with a predefined hazard radius (R_1) which is a function of the hazard type. If $d_2 \leq R_1$, the worker is too close to the hazard and an alert (combination of sound, vibration and

pop-up text) is generated. If risk factor m is negative, it is changed to zero, to make the analysis more conservative. In other words, the proposed method adjusts prediction toward the hazard, but not away from the hazard. Since the developed HMM method is aimed to improve workers' safety, adjusting the prediction by moving it away from the hazard zone may sometimes result in an impending collision which is not desirable. Next, μ is updated for the next step using the weighted average of k values from previous steps, giving higher weight to more recent k values. Specifically, μ can be determined using Equation (6).

$$\text{Aggregate Risk Factor } (\mu) = \frac{\sum_{i=1}^{n-1} k_i \times (i)}{\sum_{i=1}^{n-1} i} \quad \text{Eq. (6)}$$

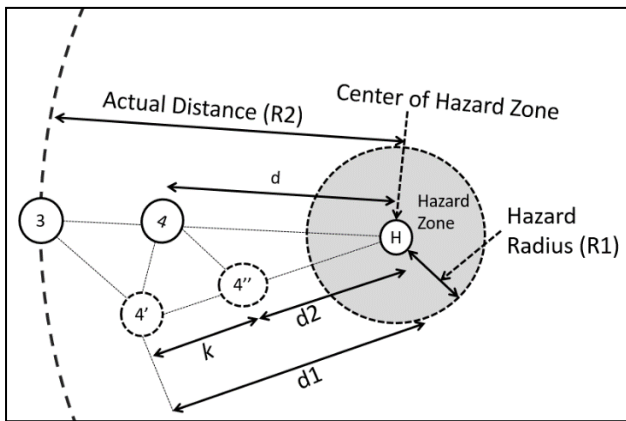


FIGURE VIII
LINEAR RISK FACTOR AND ADJUSTMENT OF PREDICTION

C. Preemptive Construction Site safety (PCS2) Mobile Application

In order to assess the practicality of the designed methodology, an Android implementation of the risk-incorporated HMM prediction model is developed and tested. This mobile application, called Preemptive Construction Site Safety (PCS2) used two radii as the boundaries of safe and unsafe region surrounding a hazard. In particular, the immediate area around a site hazard is marked by the hazard radius. Once a user enters the hazard zone, PCS2 generates a safety alert. In order to trigger the application to start computing trajectories, a wider area designated as the buffer zone is also defined around each site hazard. The values of hazard and buffer radii are specific to each type of hazard and other factors such as equipment blind spots, equipment working radii, and debris falling zones.

In each timestamp, PCS2 uses the built-in GPS sensor of the smartphone carried by the worker to locate the worker in the open space. A sensor fusion approach is adopted for triangulation using satellite, WiFi, and cellular networks to obtain more accurate positional data. The process flowchart of PCS2 is illustrated in Figure IX. Once launched (node "Start"), PCS2 accesses the GPS of the smartphone and continuously collects user's positional data. If the user does not move by a minimum distance

between two consecutive coordinates, the application considers the user stationary (i.e. not moving) and a null output is generated in response to the "Walking?" decision node. Otherwise, PCS2 stores the user's trajectory (GPS coordinates) in a SQLite database. If the user's current position is inside a buffer zone (i.e. trigger event), then PCS2's background service initiates the HMM algorithm, starts calculating corresponding risk factors, and predicts the user's risk-incorporated future position. If the predicted coordinate is inside the hazard zone, PCS2 generates and displays an alert message with vibration so that the user has enough time to assess the surroundings and adjust his or her walking trajectory accordingly.

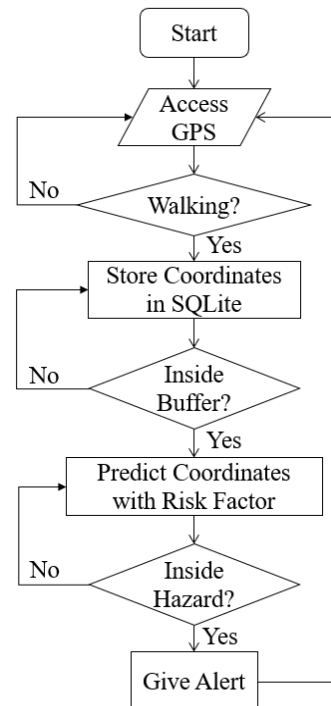


FIGURE IX
HIGH-LEVEL FLOWCHART OF PCS2 MOBILE APPLICATION

PCS2 has a user friendly graphical user interface (GUI). The GUI contains Layout XML files which are rendered as a set of View class objects. Figure X shows the mobile application layouts. The "initial layout" of the GUI allows the user to manually enter input parameters such as the number of hazard zones and input their global coordinates, hazard and buffer radii, and the prediction horizon. The "operation layout" uses Google Map in the background for real time visualization. In this layout, hazard and buffer zones are superimposed on Google Map and shown as color-coded circles. The designed GUI also plots actual, predicted, and adjusted (i.e. risk-incorporated) positions. Once a collision event occurs (adjusted position falls inside the hazard zone), the application displays an alert dialogue box and generates ringtone and vibration in the "alert layout". Finally, to support post-analysis of data, all collected data and

calculated variables can be exported to the internal phone memory in .csv format using the “export layout”.

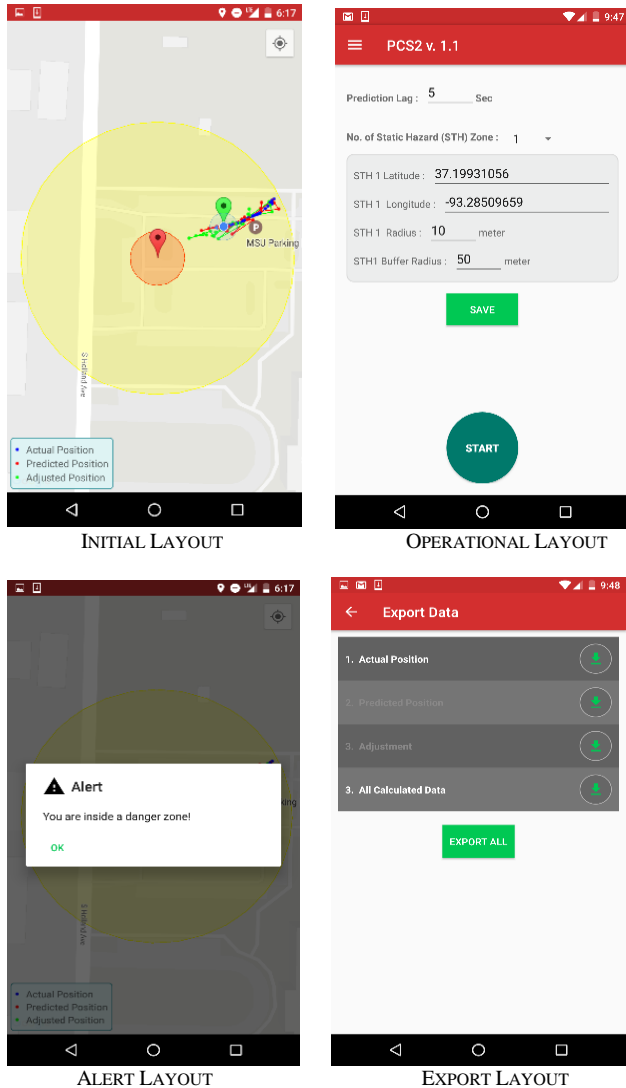


FIGURE X

SCREENSHOTS OF THE PCS2 MOBILE APPLICATION LAYOUTS

The PCS2 mobile application consists of four major Android activities. The *Main Activity* initiates the application and contains the code which calls different methods from other activities. The *Map Activity* initially allows users to input prediction lag, latitude, longitude, buffer radius, and hazard radius values. Clicking the “Save” button saves these initial values to the application. When user clicks on the “Start” button, it implements a *Location Manager* service which accesses the user’s location from the cellular network and the *GPS Provider*, through *ACCESS_COARSE_LOCATION* and *ACCESS_FINE_LOCATION*, respectively. Combining both methods results in a more accurate detection of users’ geo-location. Figure XI depicts the sequence of the function used in the mobile application to generate an alert. After collecting 12 coordinate points, the *Map Activity* implements a *normalizeSection* method to normalize the trajectory sections. If the current location is

inside the buffer zone, this activity then initiates the HMM by first implementing *getLikelihoodSection* which finds out to which latent segment does the current trajectory belong. Next, *getTransitionSegment* picks the predicted latent segment with the highest probability from the likelihood matrix. Then, it implements *getLikelihoodSection* again to identify the most likely trajectory section to be generated from the selected latent segment. Ultimately, *denormalizeSection* is implemented to calculate the 10-second real-size predicted trajectory segment. Based on the initial user input for prediction lag, the *Map Activity* stores the latitude and longitude (e.g. if the user inputs 4 seconds in the prediction lag box, *Map Activity* only stores the 4th second predicted latitude and longitude). After the initial prediction, this activity implements a *riskFactor* method to calculate the risk factor based on the hazard position, and return the adjusted prediction.

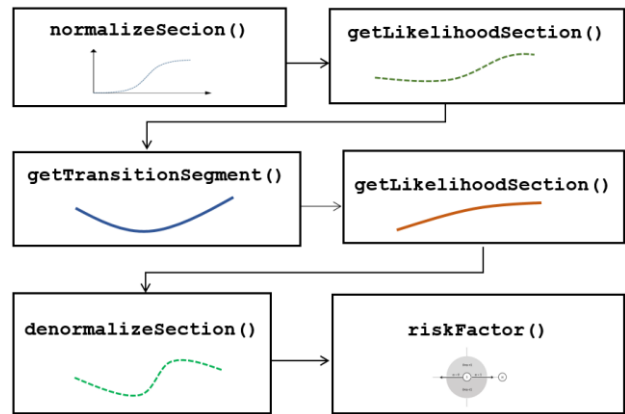


FIGURE XI

FUNCTIONS USED FOR ALERT USERS FROM THEIR LOCATION DATA

If the adjusted prediction is inside the hazard zone, it generates an alert by implementing *alertDialogueBuilder*, which also contains a *VIBRATOR_PROVIDER* to generate a physical device vibration. Besides, the *Map Activity* implements *addMarker* and *addPolylines* to display the current location, predicted location, and adjusted location using colored markers and polylines. The *Export Activity* initiates the *Export Layout* as shown in Figure X. The *SQLite* database is used to store the trained HMM matrices (transition matrix, likelihood matrix), and real-time, predicted, and adjusted user’s positions. All variables such as angular risk factor (α), linear risk factor (m), and aggregated risk factor (μ) are also stored in the database to assist data analysis. The *Export Activity* implements a *CSVwriter* class to write and store the data in a .csv file.

D. Field Validation Experiment

A field experiment is conducted to evaluate the effectiveness of the PCS2 mobile application. In the experiment, real time coordinates of a user are collected and analyzed, and a prediction based on HMM is made.

Further, the prediction is adjusted using the risk factor and if there is an impending collision, PCS2 provides a safety alert. As shown in Figure XII, the initial inputs are the coordinates of the hazard, prediction horizon, and hazard and buffer radii.

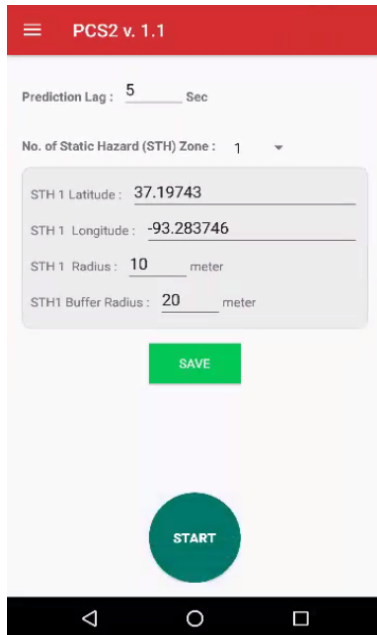


FIGURE XII
INITIAL INPUTS OF PCS2 FOR THE FIELD EXPERIMENT

Figure XIII shows the experiment setup with a user and a forklift as a stationary hazard. The hazard zone is also marked with red circle in this Figure. For this experiment, the prediction horizon (lag) is set at 5 seconds, and hazard and buffer radii are set to be 10m and 20m, respectively. The user carries a smartphone which runs the PCS2 application in the background.

Figure XIV illustrates the user’s trajectory as captured in the field. In this Figure, buffer and hazard zones around the site hazard are clearly marked. When the worker is inside the buffer zone, PCS2 starts the trajectory prediction and risk factor calculation. If the predicted location lies inside the hazard zone, a safety alert is generated and displayed. Figure XV illustrates a sample impending collision during the field experiment, where the user walked too close to the hazard and the mobile application correctly predicted an imminent collision event, and provided a timely alert to the user. In total, 15 such alerts are generated by PCS2 during this field experiment. For each alert, the exact position is marked on the ground where the alerts are given. After the experiment, 15 distances each corresponding to an alert are measured. Considering the average human walking speed (ranging between 0.5 m/s and 1.5 m/s), a 5-second advance prediction in theory should result in an alert within a distance of 12.5m to 17.5m from the hazard. If a generated alert is within 12.5m to 17.5m range, it is considered “timely”. Alerts generated when the user was closer than 12.5m are considered “late”.

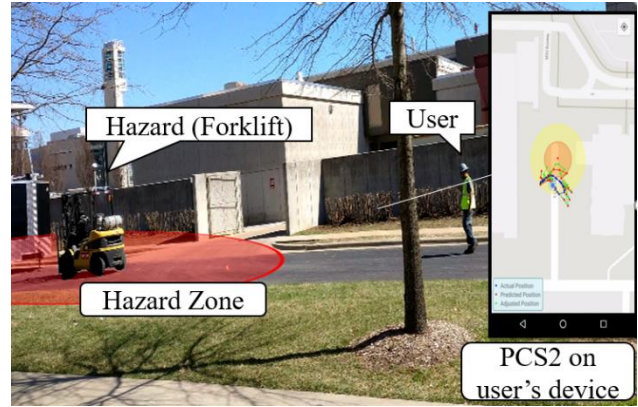


FIGURE XIII
EXPERIMENT SETUP WITH THE FORKLIFT AS A SITE HAZARD

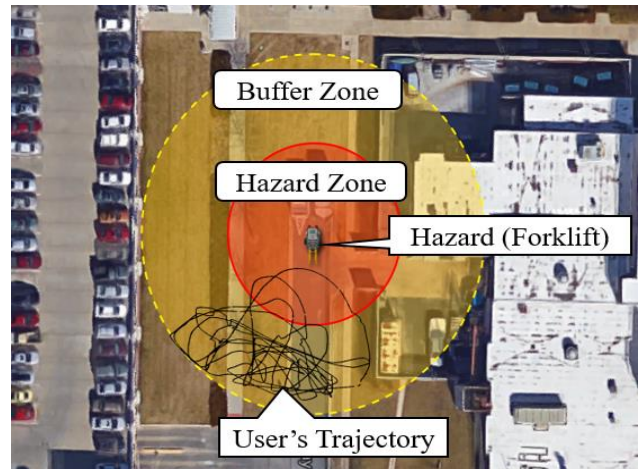


FIGURE XIV
COLLECTED USER TRAJECTORY IN THE VICINITY OF THE FORKLIFT

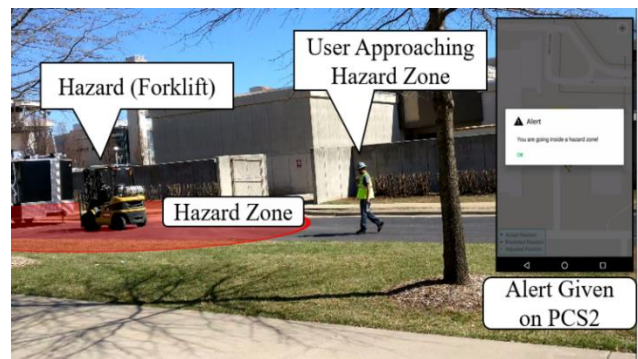


FIGURE XV
USER APPROACHING A HAZARD ZONE DURING THE FIELD EXPERIMENT

Table I summarizes the results obtained from the field experiment in terms of the timeliness of the generated safety alerts. As seen in this Table, for this particular experiment, 10 out of the total 15 generated alerts are “timely”, 5 are “late”. Nonetheless, in all 15 cases, alerts were generated prior to the user entering the hazard zone, which implies a 100% success rate. Also, recall, precision, and accuracy for the field experiment are presented in Table II. As shown in this Table, the total duration of the experiment was 448 seconds, and recall, precision, and

accuracy values were calculated as 82.5%, 68.8%, and 88.4%, respectively.

TABLE I
RESULTS OF PCS2 FIELD TEST

Alert	Distance from Hazard (meter)	Alert Timeliness (≥ 5 sec. in advance)
1	10.14	Late
2	12.9	Timely
3	12.6	Timely
4	13.72	Timely
5	10.21	Late
6	12.92	Timely
7	13.1	Timely
8	13.32	Timely
9	8.54	Late
10	12.98	Timely
11	11.3	Late
12	9.15	Late
13	13.84	Timely
14	14.47	Timely
15	12.69	Timely

TABLE II
RECALL, PRECISION, AND ACCURACY OF THE FIELD TEST

Experiment Duration (sec.)	Recall	Precision	Accuracy
448	82.5%	68.8%	88.4%

IV. LIMITATIONS & FUTURE WORK

Mobile technology including smartphones has become a ubiquitous component of daily life during the last several years. Therefore, the primary assumption of this study is that the majority of construction workers (as a subset of the general population) carry smartphones and thus, can conveniently access and launch PCS2 on their mobile devices. User friendliness and ease of use were two major design parameters when creating PCS2 interface and application features, and therefore, it is expected that future users (construction employers) will only need minimum training and supervision to successfully implement PCS2 in the field. It is imperative that since modern smartphones come equipped with a built-in GPS sensor, they can obtain context-aware information based on the global position of the device user, connectivity to available cellular networks, WiFi connection, or a combination of these methods. Each device, however, provides a different level of accuracy based on its specifications, price, and part manufacturer. According to the Institute of Navigation (ION), most of existing smartphones in the market can track their position within a 5-meter accuracy in open sky [62]. While this may be a limiting factor in the short-term implementation of PCS2, the authors believe that with the current fast pace of technological advancements in a global consumer-driven competitive market [63], such hardware challenges will be resolved in a relatively short span of time.

Future steps of this study will include enabling risk-calibrated trajectory prediction in the presence of multiple site hazards and several workers in a more complex construction environment. To facilitate the widespread adaptation of the designed methodology, large sets of trajectory data can be stored and filtered by attributes such

as type of jobs, as well as worker's age, gender, and level of experience. Such database of trajectories can significantly enhance the adaptability of the HMM to different types of projects, tasks, and workers, thus creating more reliable results. In doing so, the authors will also create more robust methods to identify, quantify, and classify potential worksite hazards, so to provide a better context for potential proximity-related accidents considering not only accident frequency (likelihood) but also accident severity [64].

V. SUMMARY & CONCLUSION

The advancement of information technology has resulted in the emergence of new mobile devices equipped with a rich set of embedded sensors capable of high level computing. Several mobile operating systems (e.g. Android, iOS) have been also developed and introduced that take advantage of high computational power and online application stores allowing developers to access a large user population worldwide. Despite these technological breakthroughs, the real value of mobile wearable sensors (e.g. smartphones) for robust position tracking in support of jobsite safety has not been yet fully investigated in the construction industry. In this research, mobile technology was deployed to design and implement a motion trajectory prediction framework for construction site safety. In particular, smartphone's GPS location services and mobile operating system were used to develop and test a native Android-based mobile application called Preemptive Construction Site Safety or PCS2 capable of real time location tracking and predicting the future location of a user. The key advantage of PCS2 is that it also incorporates individuals' risk-taking behavior in the vicinity of site hazards into trajectory prediction. A field experiment was conducted in which a stationary hazard (forklift) with buffer and hazard radii of 20m and 10m was used, and risk-incorporated trajectory predictions were made with a prediction horizon of 5 seconds. Result of the experiment showed that while PCS2 could detect all 15 impending collisions, in 10 cases, safety alerts were generated with enough lead time for the user to change course. Achieving promising preliminary results, there are several aspects of the developed prototype (e.g. software design, user interface, background mathematical formulae) that will be further improved as part of the future directions of this research so that PCS2 can be widely adopted in large-scale real-time construction site safety applications.

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