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# COUPLING RISK ATTITUDE AND MOTION DATA MINING IN A PREEMTIVE CONSTRUCTION SAFETY FRAMEWORK

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## ABSTRACT

Construction sites comprise constantly moving heterogeneous resources that operate in close proximity of each other. The sporadic nature of field tasks creates an accident prone physical space surrounding workers. Despite efforts to improve site safety using location-aware proximity sensing techniques, major scientific gaps still remain in reliably forecasting impending hazardous scenarios before they occur. In the research presented in this paper, spatiotemporal data of workers and site hazards is fused with a quantifiable model of an individual's attitude toward risk to generate proximity-based safety alerts in real time. In particular, a worker's risk index is formulated and coupled with robust hidden Markov model (HMM)-based trajectory prediction to approximate his/her future position, and detect imminent contact collisions. The designed methodology is explained and assessed using several experiments emulating interactions between site workers and hazards. Preliminary results demonstrate the effectiveness of the designed methods in robustly predicting potential collision events.

## 1 INTRODUCTION

Construction sites are dynamic and information intensive environments where resources such as personnel, equipment, and materials continuously interact with each other. This dynamic environment and random movements can lead to hazardous work conditions and contact collisions contributing to the high rate of injuries and fatalities in the construction industry. In particular, resources often move too close to each other which may constrain their operating space and freedom of movement (Sacks et al. 2009). In the absence of coordination and proper work planning, close encounters of construction resources can potentially lead to hazardous and life threatening situations. In addition, research shows that depending on the nature of the project and the level of experience and familiarity of workers with assigned tasks, the same set of tasks may present varying hazard types and sources of injury leading to different injury severities (Choe and Leite 2016). Within the construction domain, struck-by injuries (resulting from falling or suspended objects, or contact between workers and heavy equipment) are considered the main cause of fatal accidents (Esmaeili and Hallowell 2012). In addition to moving hazards (e.g., equipment), a stationary hazard (with a relatively fixed location and shape) such as a toxic, chemical, and flammable substance storage, high voltage power line, and elevated floor edge can also lead to injuries (Cheng et al. 2013). Due to the repetitive nature of most construction tasks workers often experience decreased awareness and lack of focus (Pratt et al. 2001). Obstruction of equipment operators' visibility, specifically blind spots also contributes to contact collisions (Fullerton et al. 2009). Although there has been extensive research on proximity-related safety issues in construction, figures reveal that work-related injuries and fatalities are still a major problem in the industry.

Existing safety measures mainly strive to enforce industry standards and regulations such as those of the Occupational Safety and Health Administration (OSHA) (OSHA 2016). These practices, however, are considered passive safety techniques that can easily fail to give timely warnings in advance of an accident taking place. It is therefore necessary to design and implement real time, proactive safety methods that can track the location of construction resources and generate safety alerts ahead of an imminent collision. While a number of previous studies have aimed at designing methods for estimating the position of construction resources using means such as trajectory prediction, a key issue that has been mostly overlooked is the integration of workers' risk attitude into the prediction. In the context of this research, the attitude toward risk is defined as a measure of affinity for or aversion to risky behavior near hazards. Past research has indicated that factors including age, gender, experience level, peer pressure, and social norms play an important role in how a person performs his/her daily activities (Salminen 2004, Gardner and Steinberg 2005, Charness and Gneezy 2012). In addition, a recent study has concluded that when operating in a certain location, a construction worker's bodily response is highly correlated with the likely presence of a safety hazard in that location (Kim et al. 2016).

In light of this, the work presented in this paper aims at improving the current practice of construction safety monitoring by designing and systematically evaluating a safety monitoring framework that couples real time positional data, trajectory prediction, and attitude toward risk in the vicinity of site hazards. In particular, a robust trajectory prediction technique based on hidden Markov model (HMM) is formulated and tested, and further improved and customized for each worker by incorporating his/her risk attitude parameters (i.e. linear and angular risk factors). In addition, precision-recall analysis is conducted for trajectories of different shape and complexity to determine the effectiveness of the prediction model in the presence of both stationary and moving site hazards. Moreover, to assess the applicability of the designed methodology to real world situations, a mobile application is developed and tested in a number of field experiments.

## 2 LITERATURE REVIEW

Construction workers are often exposed to potentially hazardous elements such as moving equipment, heavy tools and machinery, and harmful substances. OSHA refers to the main causes behind construction-related injuries as the "Fatal Four" (falls, electrocutions, struck by object, caught-in/between). In 2015, the fatality rate in construction was reported as 10.1 per 100,000 full-time equivalent (FTE) workers, compared to the average worker fatality rate of 3.4 per 100,000 FTE workers across all industries. In particular, in 2015, 937 of a total of 4379 construction worker fatalities (21.4%) resulted in a loss of life, which is the highest level since 2008 (BLS 2016). Eliminating the root causes of "Fatal Four" incidents can potentially save the lives of 602 workers every year (OSHA 2016). In 2002, the total cost of fatal and non-fatal injuries in the construction industry was estimated at $11.5 billion. The average cost per case was $27,000, almost double the per case cost of $15,000 for all other industries (Waehrer et al. 2007). Due to the extremely dynamic and complex environment of construction sites and the diversity and nature of project tasks, it is very difficult for safety inspectors to continuously monitor and identify every incident that may put workers at risk (Park et al. 2016).

Teizer et al. (2010) identified proximity between resources as one of the distinct safety problems in construction sites. Accidents resulting from close proximity of objects and workers are often characterized as contact collisions. With recent advancements of sensing technologies and wearable devices, efforts have been made to develop proactive proximity safety warning systems for construction workers. To identify workers exposed to safety risks based on the location or proximity information, researchers have previously used a host of sensing systems such as Bluetooth (Park et al. 2016), ultra-wide band (UWB) (Yang et al. 2011), global positioning system (GPS) (Wu et al. 2013), radio frequency identification (RFID) (Goodrum et al. 2006, Teizer et al. 2010), video camera (Yang et al. 2011), and magnetic proximity sensing (Fang et al. 2016). Teizer et al. (2010) designed a system using radio frequency (RF) which gives an audio-visual alert to workers and equipment operators when they get too close to one another. Other researchers have experimented the viability of RFID sensors by tracking the location of workers, equipment, and materials to prevent unwanted accidents from struck by falling objects (Wu et al. 2013). In another project, Wu et al. (2013) combined wireless communication, GPS, and geographic information system (GIS) in a real time safety warning system that detects hazards, alerts drivers to avoid collisions, and ultimately ensures reliable navigation of construction equipment. Coupling visualization and UWB data collection, Li et al. (2016) developed a construction safety and monitoring system to prevent equipment collisions and simultaneously track workers' and equipment locations. It was cited, however, that interruptions in the local area network (LAN) connection may hinder the ability of the system to operate continuously. Park et al. (2016) presented a safety framework by integrating the Bluetooth low-energy (BLE)-based location detection technology with a building information modeling (BIM)-based hazard identification and a cloud-based communication platform. However, their system yielded unsatisfactoy results specifically at the transition of hazard boundaries.

In addition to operational inefficiencies as identified above, the upfront costs associated with the procurement, installation, operation, and maintenance of most sensing systems may hinder their full adoption in the construction industry. Therefore, this research investigates an alternative approach to site safety by exploring the potentials of ubiquitous smartphones as data collection and information delivery platforms. Smartphones are equipped with a wide range of built-in sensing devices, can operate without the need to communicate with any preinstalled infrastructure on the jobsite, are ubiquitous (almost everybody owns and knows how to operate one), are cost effective (no extra hardware or software needs to be purchased), and cause minimum distraction and discomfort to the crew. When carried by a construction worker, smartphone's GPS sensor can be used for position tracking in support of location-aware information delivery (e.g. generating and displaying safety alerts).

Although the mere position tracking of construction resources can add value to any safety application, the safety environment on a jobsite can be further improved by taking advantage of a robust trajectory prediction model that enables the application to approximate the immediate future trajectory of an object based on its previous movement path. Trajectory prediction methods can be generally divided into two categories: classification techniques in which a mathematical trajectory is built in order to predict one's future position, and goal-oriented techniques in which human moves are predicted considering the ultimate objective of the performed task (Ferrer and Sanfeliu 2011). Trajectory prediction has been explored in different scientific and engineering disciplines. For instance, Ayhan and Samet (2016) presented a stochastic trajectory prediction approach using HMM for air traffic management (ATM) to plan fuel efficient flight paths and assist airspace flow management, ultimately resulting in higher safety, capacity, and lower emission. In another study, researchers proposed recurrent neural network (RNN) models for human trajectory prediction in crowded spaces (Alahi et al. 2016). A large body of work on trajectory prediction exists in the area of robotics research. For instance, Hamasaki et al. (2011) designed a pedestrian movement prediction system to prevent collisions of mobile robots. Most of the trajectory prediction algorithms are based on the clustering technique where a prediction is made by analyzing the discovered historical motion patterns. For example, Luo and Berenson (2015) used Gaussian mixture models (GMM), a cluster-based technique, for human motion recognition and early prediction. According to their hypothesis, if a portion of a trajectory is given, then the remainder of the trajectory can be predicted by first determining to what GMM it belongs, and then using Gaussian mixture regression to predict the remainder of the trajectory. However, in the presence of random movements in an unstructured environment (e.g. human workers on a construction jobsite), where subjects are conscious and can make split-second decisions to change course, a purely mathematical cluster-based trajectory prediction model may fail to generate adequate results. In this work, to achieve better results that are more sensitive to each individual worker and his/her behavioral traits, attitude toward risk (a cognitive measure) is another key element that is quantified, formulated, and used.

Considering these scientific gaps in knowledge and the potential of mobile technologies to improve construction safety, the goal of this research is to develop, test, and validate a real time predictive proximity alert system to improve safety on construction sites. To achieve this goal, first, a robust HMM-based trajectory prediction model is developed. Random trajectories are collected and used to train the HMM before it is used predict the shape of a new trajectory streamed from the GPS sensor of a worker's smartphone. Next, a conglomeration of factors (a.k.a risk profile) is considered to refine the predicted trajectory. Finally, the refined predicted trajectory is checked against the location of site hazards. An impending collision event is logged and a safety alert is generated if the worker's predicted position is within a certain distance of a hazard. This paper also investigates how much in advance can a worker be reliably warned of hazardous encounters (e.g. close proximities) to avoid an accident. It is imperative that sending a warning message to a worker who is already too close to a hazard may not serve the purpose. Another important contribution of this research is the incorporation of a person's risk profile with the prediction model which ensures a personalized solution for each worker.

## 3 RESEARCH METHODOLOGY

As explained earlier, the developed methodology uses sensor data (smartphone GPS), coupled with a worker's risk profile to predict his/her immediate future position, and generate safety alerts if he or she is in close proximity to hazards. For this purpose, and after evaluating a host of trajectory prediction methods, HMM was ultimately selected in this research. The model was trained and further calibrated using individuals' risk profiles, and successfully tested to predict imminent collisions. Details of the developed methodology are explained below.

### 3.1 Trajectory Prediction Using Hidden Markov Model (HMM)

HMM is developed and examined where trajectories are considered as discrete stochastic processes. A moving object's trajectory can be broken down into a number of short trajectory sections. Short sections with common statistical features (e.g. mean, variance, and covariance) are bundled into one cluster which is represented by a single average section (a.k.a. latent segment) (Choi and Hebert 2006). The limited horizon assumption, a fundamental HMM principle, states that the probability of a future location depends only on the current location and not on the path by which this current location has been achieved (Ramage 2007). In essence, an individual's choice of direction and pace of next move can be sufficiently explained by considering his/her current location and the way that individual perceives his/her surroundings. Thus, given a sequence of latent segments $S_0$, $S_1$, $S_2$,….$S_n$ the probability of a future latent segment, $S_{n+1}$ depends only on the current latent segment, $S_n$, as stated in Equation (1),

$$P(S_{n+1} \mid S_n, S_{n-1}, S_{n-2} \ldots\ldots S_0) = P(S_{n+1} \mid S_n) \tag{1}$$

In HMM, these probabilities are termed transition probabilities and together create the transition matrix. Within a cluster of sections, the likelihood of a trajectory section to be generated from a specific latent segment is calculated from the bivariate normal probability density function. These likelihood values are stored in the likelihood matrix. The HMM is trained to compute normalized trajectory sections, latent segments, and transition and likelihood matrices. The model first checks the likelihood matrix to find 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 picks the most likely trajectory segment from the likelihood matrix. The relationship between observed short trajectory segments and their associated latent segments throughout the trajectory is shown in Figure 1.

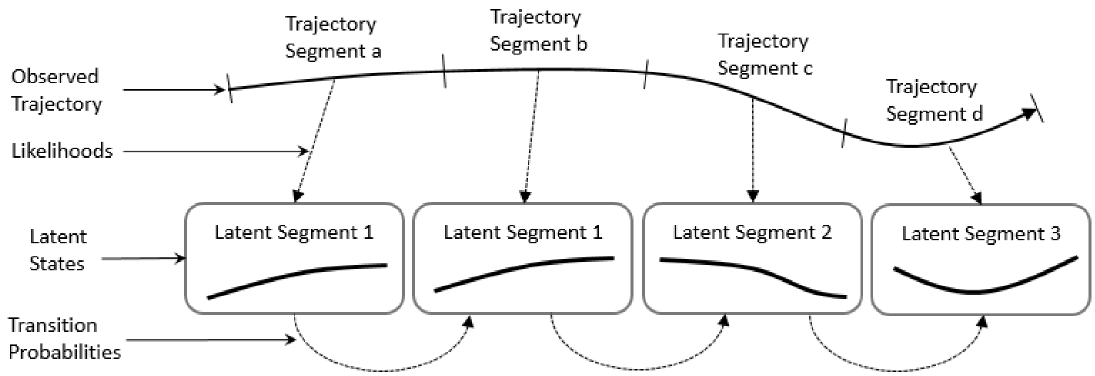



Figure 1. Relationship between observed trajectory, segments, likelihoods, latent states, and transition probabilities.

### 3.2 Learning Latent Segments

A total of 26 individuals participated in the training data collection process and 1,166 minutes of trajectory data (latitude, longitude) with 1 Hz frequency was collected. Each trajectory is divided into 12-second short sections. Each section is first translated to the origin (0, 0), rotated so that the initial direction is (1, 0), and finally scaled so that the initial velocity is unit velocity. This process is done to normalize all short sections, and results in 4,622 normalized short trajectory sections. Each short trajectory section is represented by a 22-dimensional vector consisting of $x$ and $y$ coordinates at 1-second intervals. Next, K-means clustering (Choi and Hebert 2006) is applied to find statistically similar trajectory sections. For the collected trajectory data in this research, 8 clusters were found to best represent all short trajectory sections. Each cluster is described by a single latent segment the attributes of which are contained in a 5-by-12 characteristics matrix. In particular, five statistical features (means, variances, and covariance of $x$ and $y$ coordinates) are calculated for 12 data points (times $t_1$, $t_2$,….,$t_{12}$) of all trajectory segments in a cluster.

### 3.3 HMM Training and Prediction

The training process of the HMM is illustrated in Figure 2. The first step of training the HMM is calculating the transition probabilities between all latent segments. In this research, transition probabilities form an 8-by-8 matrix (since there are 8 clusters). Each row of this matrix contains the probabilities of one latent segment to be followed by other latent segments. Next, the likelihood of a normalized section to be generated from a latent segment is calculated. A bivariate normal probability density function is used to calculate the likelihoods. From Bayes theorem, it can be said that the latent segment with the highest probability of generating a trajectory section is the one with the highest likelihood.

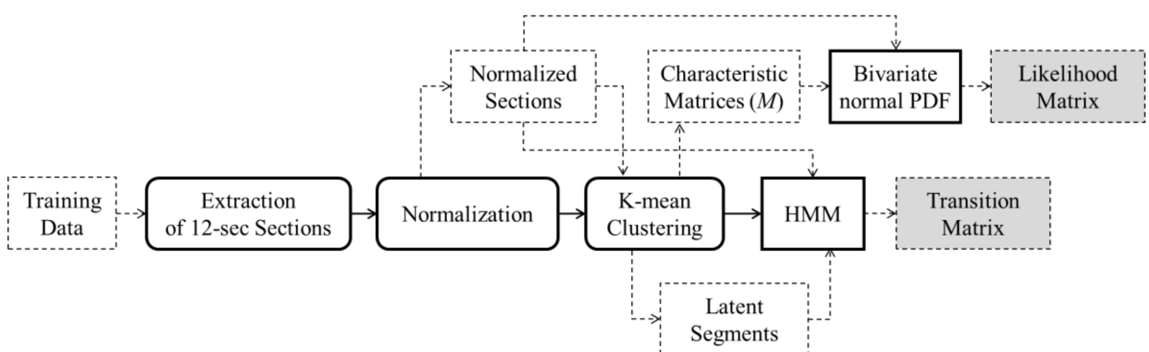



Figure 2. Input-process-output diagram of HMM training stage.

Since each segment consists of 12 data points, at least 12 points are required to create one segment and launch the prediction model. The prediction process is shown in Figure 3 which starts by observing and normalizing the latest segment ($l_n$) which contains the last 12 data points. Next, the likelihood matrix is used to select the latent segment ($S_n$) that most closely resembles the normalized segment (maximum likelihood probability). Then, the most probable next latent segment ($S_{n+1}$) is computed from the transition matrix. Subsequently, the likelihood matrix is used to find the trajectory segment which is most likely to be generated from $S_{n+1}$. Finally, the trajectory segment is de-normalized to generate the predicted future trajectory ($l_{n+1}$). The first two points of $l_{n+1}$ are patched to the existing trajectory. Therefore, the HMM model can predict up to 10 seconds in advance.

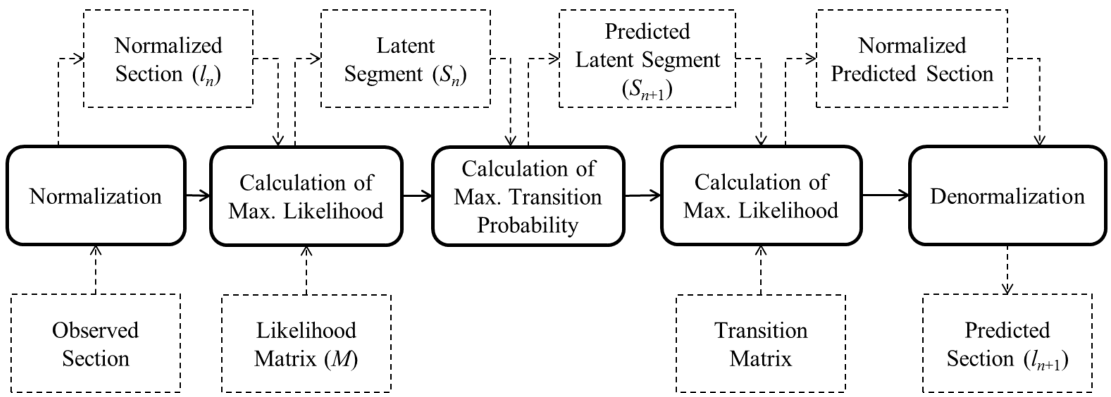



Figure 3. Input-process-output diagram of HMM prediction stage.

### 3.4 Incorporating Risk-Taking Behavior into Trajectory Prediction

The developed HMM trajectory prediction method explained so far provides a first good estimate of a worker's immediate future position given his/her past movement patterns. As stated in Subsection 3.2, the collected training data were completely random and not influenced by project-specific factors such as site layout, equipment layout, and job type, thus putting less constraints on the HMM. This puts less constraints on the prediction model and makes it more generalizable to a variety of situations. In order to customize this benchmark HMM for specific job types and individuals, attribute toward risk was formulated and integrated into the developed HMM. In general, for a risk-taker person, the predicted future location is moved closer to the hazard since he or she is more likely to be on a collision course. Two types of risk factors are considered: angular risk factor ($\alpha$), and linear risk factor ($m$). The overall risk factor ($k$) is the product of angular and linear risk factors. To yield best results, it is important to properly quantify the risk attitude (referred to in this paper as the aggregate risk factor or $\mu$) of each worker. An individual's aggregate risk factor is calculated and updated based on the history of his/her movements in the vicinity of hazards. In particular, $\alpha$ is calculated based on the worker's actual path. If a worker moves directly toward the hazard, $\alpha$ is 1 (risk-taker), and if he or she moves in the opposite direction of the hazard, $\alpha$ is 0 (risk-averse). For all other directions of move, $\alpha$ varies between 0 and 1. The linear risk factor ($m$), on the other hand, is based on the linear distance between predicted and actual positions, and represents how much radial error the prediction has relative to the worker's actual position, with the hazard zone (H) in the center of the circle. In Figure 4, the predicted position is shown as 4′. Distances $d$ between actual position (4) and hazard, and $d_1$ between 4′ and hazard can be calculated using the haversine formula. Given $d$ and $d_1$, $k$ is calculated using Equation (2). Initially, $\mu$ is set at zero and workers are all assumed to be neutral (neither risk-taker nor risk-averse). This parameter will be modified over time for each worker as new positional data is collected. In the next iteration, point 4′ is shifted $k$ units toward H. The adjusted position is labeled 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 is generated. If risk factor $m$ is negative, it is adjusted to zero, resulting in $4''=4'$, making the analysis more conservative. Next, $\mu$ is updated for the next step using the weighted average of $k$ values from previous steps.

$$Risk\ Factor\ (k) = \alpha \times m = \alpha \times (d_1 - d) \tag{2}$$

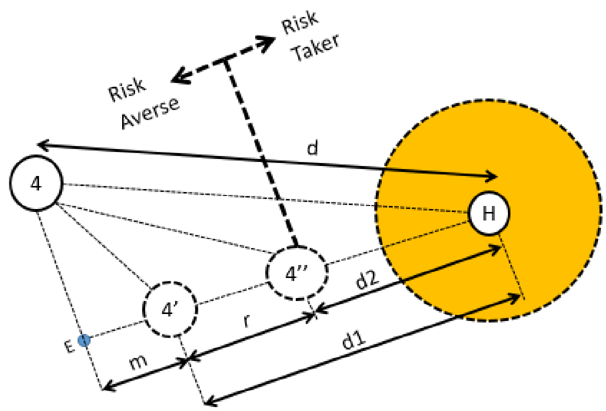


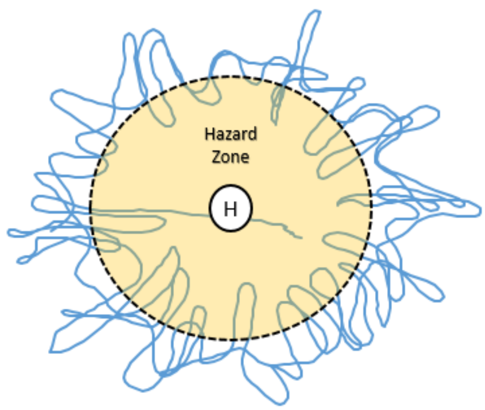

Figure 4. Linear risk factor and adjustment of predicted position.

## 4 EXPERIMENTS AND RESULTS

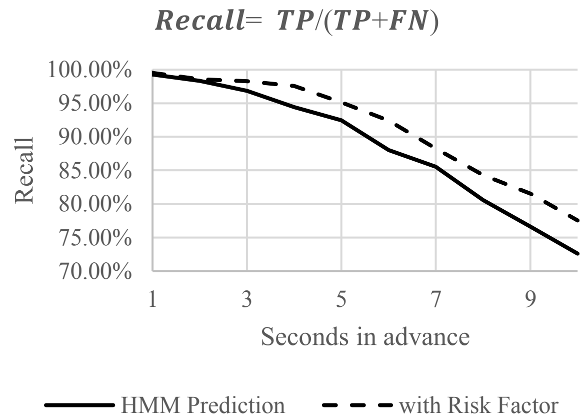
### 4.1 Evaluating the Robustness of the Trajectory Prediction Method

To evaluate the robustness of the developed HMM prediction model in safety-related scenarios, several experiments were conducted with both stationary and moving site hazards. In each experiment, worker's GPS position was recorded for 15 minutes by an android application with a frequency of 1 Hz (one positional data per second). In this Section, a scenario involving a stationary hazard zone (e.g. point H in Figure 5(a)) is described. In all experiments, the safety alert system is triggered when the worker is inside a buffer radius ($R_2$). The buffer radius is selected to be 45.7 m (150 ft) from the center of the hazard. In addition, every time the worker's distance to the hazard is less than the hazard radius ($R_1$) of 30.5 m (100 ft) a collision event is logged. The values for $R_1$ and $R_2$ are initially selected by educated guess, but can be modified depending on the situation and type of hazard, equipment blind spots (Hefner and Breen 2004), or severity of a potential collision. Worker's trajectory in and around the hazard zone is illustrated in Figure 5(a). Initially, a prediction is made using the trained HMM to estimate the worker's future position in 1 to 10 seconds in advance. Next, risk attitude is factored in to adjust the predicted position. A precision-recall analysis is then conducted to determine the reliability of the prediction model. For this analysis, any data point inside the buffer zone is considered an event, and four indicators, namely the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are used to calculate three performance measures: precision, recall, and accuracy. A TP event is when the algorithm correctly identifies that a worker is inside the hazard zone, a TN event is when the algorithm correctly identifies that the worker is outside the hazard zone, a FP event is when the algorithm falsely identifies that a worker is inside the hazard zone, and a FN event is when the algorithm falsely identifies that a worker is outside the hazard zone.

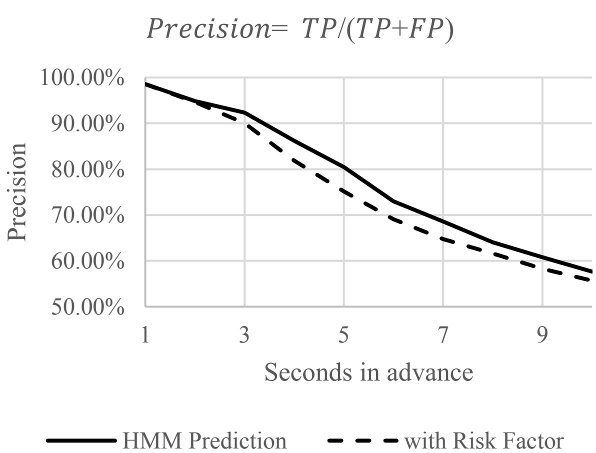
Figures 5(b), 5(c), and 5(d) show that recall, precision, and accuracy decrease with an increase in the prediction horizon. This can be attributed to the resulting increase in the uncertainty of trajectory prediction. Figure 5(b) shows that recall increases when risk is factored in the trajectory prediction. By incorporating the risk factor, the predicted position is further moved toward or away from the hazard. Due to this adjustment, more FP events are generated which can cause a slight decrease in precision as well as in accuracy. For instance, for a 5-second risk-incorporated advance prediction, recall increases by 2.5% (from ~92.5% to ~95%) while accuracy decreases by 2% (from ~87% to ~89%).



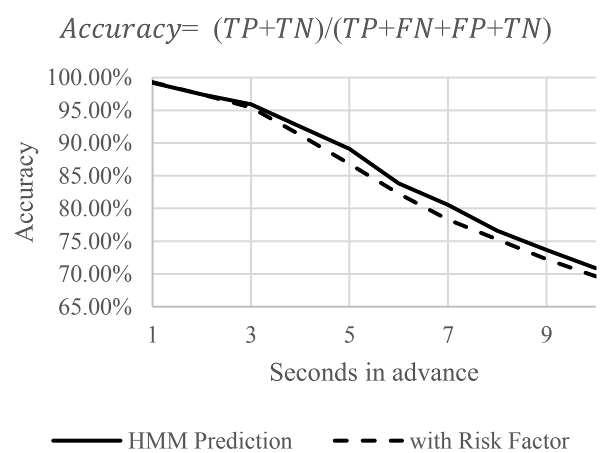

(a) Motion trajectory and stationary hazard




(b) Recall variation vs. prediction horizon




(c) Precision variation vs. prediction horizon

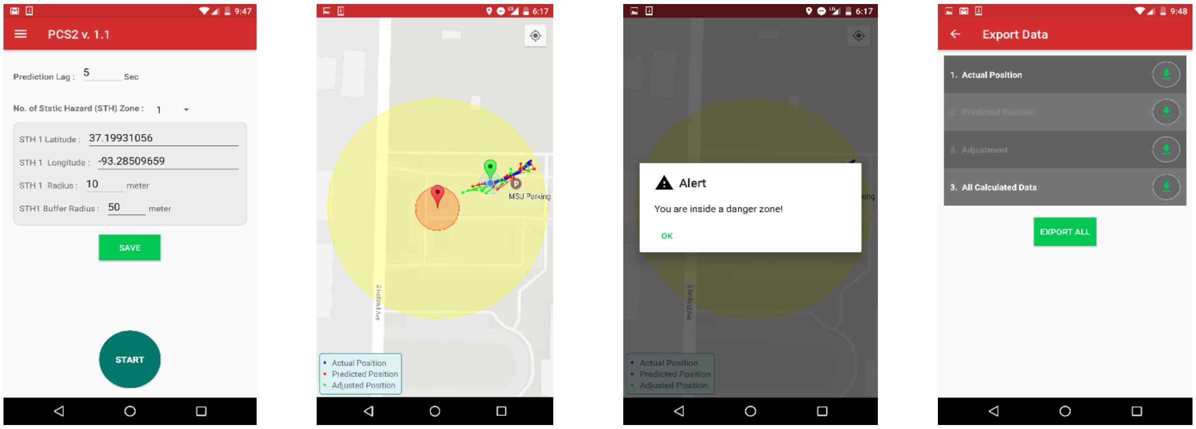



(d) Accuracy variation vs. prediction horizon

Figure 5. Stationary hazard experiment and recall, precision, and accuracy analyses.

### 4.2 Preemptive Construction Site Safety (PCS2) Mobile Application

Having achieved promising results in the preliminary experiments, a mobile application, "Preemptive Construction Site Safety (PCS2)" was subsequently developed to test the designed methodology in the field, and evaluate its applicability to real world scenarios. Figure 6 shows the main user interface of PCS2 in four different modes (initial, operation, alert, and export). Further details of the developed mobile application can be found in Rashid (2017). Next, field experiments were conducted to evaluate the effectiveness of the PCS2 application. Figure 7 shows one such experiment in which the prediction horizon was set at 5 seconds, a forklift was used as a stationary hazard, and hazard and buffer radii were selected to be 10m and 20m, respectively. User's GPS coordinates were collected and analyzed in real time by PCS2, and trajectory prediction was made with time using the trained HMM. This prediction was further adjusted considering the latest risk factor calculated in real time. As soon as an impending collision was detected, a safety warning (combination of text, vibration, and sound alerts) was generated and delivered to the user.




Initial layout Operation layout Alert layout Export layout

Figure 6. User interface of the PCS2 mobile application developed in this research.

Figure 7 illustrates the experiment setup showing an impending collision, where the user got 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 were generated by PCS2 during the experiment. For each alert, the exact position was marked on the ground where the alert was given. After the experiment, 15 distances each corresponding to an alert were 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. An alert generated within this range is considered ideal (neither too early nor too late). Table 1 summarizes 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 were generated when the worker was more than 5 seconds away from the hazard.


Figure 7. Setup of the field experiment showing the worker approaching a stationary hazard.

Table 1. Analysis of generated alerts by PCS2 mobile application.

| Alert | Distance from Hazard (m) | Time to Hazard (sec) |
|---|---|---|
| 1 | 10.14 | < 5 |
| 2 | 12.9 | > 5 |
| 3 | 12.6 | > 5 |
| 4 | 13.72 | > 5 |
| 5 | 10.21 | < 5 |
| 6 | 12.92 | > 5 |
| 7 | 13.1 | > 5 |
| 8 | 13.32 | > 5 |
| 9 | 8.54 | < 5 |
| 10 | 12.98 | > 5 |
| 11 | 11.3 | < 5 |
| 12 | 9.15 | < 5 |
| 13 | 13.84 | > 5 |
| 14 | 14.47 | > 5 |
| 15 | 12.69 | > 5 |

## 4. SUMMARY AND CONCLUSIONS

This paper presented a methodology for designing, testing, and evaluating a new proximity safety alert framework for construction sites. The designed technique coupled trajectory prediction and individuals' attitude toward risk. In particular, a HMM was developed and trained to predict a worker's future position in the vicinity of site hazards using streaming GPS data from the worker's smartphone. This initial prediction was further adjusted by quantifying and factoring in the individual's risk attitude (a measure of affinity for or aversion to risky behavior near hazards). The advantage of using HMM for trajectory prediction is that HMM is a self-learning technique that can adapt to real world situations as more streaming data are received. Experiments were carried out and precision, recall, and accuracy analyses were conducted to test the effectiveness of the designed methodology. In these experiments, hazard zones were assumed to be in fixed positions, and hazard and buffer radii were defined around each hazard location. Results indicated that the incorporation of risk attitude in motion trajectory prediction results in higher recall values while slightly decreases accuracy and precision. Next, an android-based mobile application (PCS2) was developed and a field experiment was conducted to test the robustness of this application. Results demonstrated the potential value of adapting the developed mobile safety framework to enhance crew safety. In addition to its ubiquity and cost effectiveness, the advantage of using smartphones in the designed framework is that they do not rely on preinstalled infrastructure on the jobsite and can mitigate potential discomfort to the crew that bulky headsets or head mounted displays (HMDs) would cause. Overall, the findings of this research contribute to the current knowledge and practice by advancing the application of wearable technology and construction data analytics in construction safety. Future work in this research will include experimenting with multiple (stationary and moving) hazards and workers in more complex settings.

## ACKNOWLEDGMENTS

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**REFERENCES**

Alahi, A., K. Goel, V. Ramanathan, A. Robicquet, L. Fei-Fei, and S. Savarese. 2016. “Social lstm: Human Trajectory Prediction in Crowded Spaces.” In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 961-971.

Ayhan, S., and H. Samet. 2016. “Aircraft Trajectory Prediction Made Easy with Predictive Analytics." In *Proceedings of the 22nd International Conference on Knowledge Discovery and Data Mining*.

BLS. 2016. “National Census of Fatal Occupational Injuries in 2015.” U.S. Department of Labor. News Release 16 December 2016 https://www.bls.gov/news.release/pdf/cfoi.pdf.

Charness, G. and U. Gneezy. 2012. “Strong Evidence for Gender Differences in Risk Taking.” *Journal of Economic Behavior & Organization* 83.1:50-58.

Cheng, T., N. Pradhananga, and J. Teizer. 2013. “Automated Evaluation of Proximity Hazards Caused By Workers Interacting With Equipment.” In *Proceedings of the 30th ISARC*, Montreal, Canada.

Choi P. P., and M. Hebert. 2006. “Learning and predicting moving object trajectory: a piecewise trajectory segment approach.” *Robotics Institute*. 337.

Choe, S., and F. Leite. 2016. “Assessing Safety Risk among Different Construction Trades: Quantitative Approach.” *Journal of Construction Engineering and Management*, 04016133.

Esmaeili, B., and M. R. Hallowell. 2012. “Attribute-based risk model for measuring safety risk of struck-by accidents.” *Construction Research Congress 2012: Construction Challenges in a Flat World*.

Fang, Y., Cho, Y. K., & Chen, J. 2016. “A framework for real-time pro-active safety assistance for mobile crane lifting operations.” *Automation in Construction*, 72, 367-379.

Fullerton, C. E., B. S. Allread, and J. Teizer. 2009. “Pro-active real-time personnel warning system.” *Pro-active real-time personnel warning system.* 31-40.

Ferrer, G., and A. Sanfeliu. 2011. “Comparative analysis of human motion trajectory prediction using minimum variance curvature.” In *Proceedings of the 6th international conference on Human-robot interaction*. ACM.

Gardner, M. and L. Steinberg. 2005. “Peer influence on risk taking, risk preference, and risky decision making in adolescence and adulthood: an experimental study.” *Developmental psychology* 41.4: 625.

Goodrum, P. M., M. A. McLaren and A. Durfee. 2006. “The application of active radio frequency identification technology for tool tracking on construction job sites.” *Automation in Construction* 15.3: 292-302.

Hefner, R., and P. J, Breen. 2004. “Construction vehicle and equipment blind area diagrams.” National Institute for Occupational Safety and Health, Report, 200-2002, 00563.

Hamasaki, S., Y. Tamura, A. Yamashita, and H. Asama. 2011. “Prediction of human's movement for collision avoidance of mobile robot.” *Robotics and Biomimetics (ROBIO), 2011 IEEE International Conference on. IEEE.*

Kim, H., C. R. Ahn, and Y. Kanghyeok. 2016. “Identifying Safety Hazards Using Collective Bodily Responses of Workers.” *Journal of Construction Engineering and Management*, 04016090.

Li, H., G. Chan, J. K. W. Wong, and M. Skitmore. 2016. “Real-time locating systems applications in construction.” *Automation in Construction* 63:37-47.

Luo, R., and D. Berenson. 2015. “A framework for unsupervised online human reaching motion recognition and early prediction.” *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).*

OSHA. U.S. Department of Labor. 27 May 2016. https://www.osha.gov/oshstats/commonstats.html.

Pratt, S. G., D. E. Fosbroke, and S. M. Marsh. 2001. “Building safer highway work zones: Measures to prevent worker injuries from vehicles and equipment”. DHHS (NIOSH) Publication, No. 2001-128

Park, J. W., K. Kim, and Y. K. Cho. 2016. “Framework of Automated Construction-Safety Monitoring Using Cloud-Enabled BIM and BLE Mobile Tracking Sensors.” *Journal of Construction Engineering and Management*, 05016019.

Ramage, D. 2007. "Hidden Markov models fundamentals." Lecture Notes. http://cs229. stanford. edu/section/cs229-hmm. pdf.

Rashid, K. M. 2017. "Coupling Mobile Technology, Position Data Mining, and Attitude toward Risk to Improve Construction Site Safety". M.Sc. thesis, Department of Technology and Construction Management, Missouri State University, Springfield, Missouri, USA.

Sacks, R., O. Rozenfeld, and Y. Rosenfeld. 2009. "Spatial & temporal Exposure To Safety Sazards In Construction." *Journal of contruction engineering and management* 135.8: 726-736.

Salminen, S. 2004. "Have Young Workers More Injuries than Older Ones?" An International Literature Review. *Journal of safety research* 35.5:513-521.

Teizer, J., S. A. Ben, E. F. Clare, and H. Jimmie. 2010. "Autonomous pro-active real-time construction worker and equipment operator proximity safety alert system." *Automation in construction* 19.5: 630-640.

Wu, H., J. Tao, X. Li, X. Chi, H. Li, X. Hua, R. Yang, S. Wang, and N. A. Chen. 2013. "A location based service approach for collision warning systems in concrete dam construction." *Safety science* 51.1: 338-346.

Waehrer, G.M., X. S. Dong, T. Miller, E. Haile, and Y. Men. 2007. "Costs of occupational injuries in construction in the United States." *Accident Analysis & Prevention* 39.6: 1258-1266.

Yang, J., T. Cheng, J. Teizer, P. A. Vela, and Z. K. Shi. 2011. "A performance evaluation of vision and radio frequency tracking methods for interacting workforce." *Advanced Engineering Informatics* 25.4: 736-747.

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