



Stochastic state sequence model to predict construction site safety states through Real-Time Location Systems



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ABSTRACT

This paper addresses the challenge to design an effective method for managers to efficiently process hazardous states via recorded historical data by developing a stochastic state sequence model to predict discrete safety states – represent the hazardous level of a project or individual person over a period of time through a Real-Time Location System (RTLS) on construction sites. This involves a mathematical model for state prediction that is suitable for the big-data environment of modern complex construction projects. Firstly, an algorithm is constructed for extracting incidents from pre-analysis of the walk-paths of site workers based on RTLS. The algorithm builds three categories of hazardous region distribution – certain static, uncertain static and uncertain dynamic – and employs a frequency and duration filter to remove noise and misreads. Key regions are identified as either ‘hazardous’, ‘risky’, ‘admonitory’ or ‘safe’ depending on the extent of the hazard zone from the object’s boundary, and state recognition is established by measuring incidents occurring per day and classifies personal and project states into ‘normal’, ‘incident’, ‘near-miss’ and ‘accident’. A Discrete-Time Markov Chain (DTMC) mathematical model, focusing on the interrelationship between states, is developed to predict states on construction sites. Finally, a case study is provided to demonstrate how the system can assist in monitoring discrete states and which indicates it is feasible for the construction industry.

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1. Introduction

Modern construction industry systems, especially in large and specific projects are highly complex with numerous interrelated processes, workers and hazardous worksites. Real-time monitoring of workers’ behavior is necessary for responding to (and preventing) project disruption, accidents and injuries in a timely manner. However, although process innovation and advances in technology have been demonstrated to improve safety management and labor productivity on construction projects (Akinci et al., 2006; Gordon and Akinci, 2005; Jaselskis and El-Misalami, 2003), such timely prediction or advanced warning of accidents remains problematic (Wang and Razavi, 2015; Wu et al., 2010a). It is such a nuisance raising 59% false or negative alarms during a 7-day test (Ruff,

2006) that operators are prone to lose confidence and ignore the alarms hereafter (Bliss et al., 1995).

The development and extensive use of Radio Frequency Identification (RFID), Ultra Wideband (UWB) and Bluetooth Low Energy (BLE) has improved location tracking for allocating labor, materials and equipment resources more effectively and safely (Teizer et al., 2008) and the maturity of Real-Time Location Systems (RTLS) technology has resulted in cost reductions and improved data accuracy and integrity. RTLS and Physiological Status Monitoring (PSM) have also been used as an effective tool to remotely monitor the health (Altini et al., 2014; Wang et al., 2015) and safety of the construction workforce (Bates and Schneider, 2008; Cheng et al., 2013). This integrates data from the construction workers’ location and physiological status to automatically identify unsafe work behaviors as accident precursors. However, despite technological improvements in RTLS, construction projects still suffer from unexpected disruptions and delays due to worker injuries. Only major accidents are currently reported amongst the big data stored and do not include the large number of near-misses and minor injuries which constitute the major portion of unreported safety issues

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(Dee et al., 2013; Taylor et al., 2014; Wu et al., 2010b; Yang et al., 2014).

A near-miss is an incident which has the capacity to cause an accident or injury, but fortunately did not happen (Marsh and Kendrick, 2000). If regular near-miss incidents are left unaddressed, they can escalate into serious safety accidents on construction sites. Thus, the identification of near-misses can provide insights into the potential risk of future accidents. Moreover, near-misses and minor injuries on construction sites occur at a much higher rate than more severe accidents (Heinrich et al., 1950; Wu et al., 2010b). As Fig. 1 reveals frequency of accidents is inversely and non-linearly proportional to severity. The horizontal axis representing accident severity ranges from 0 (no injuries) to max (fatalities) based on hazard identification index (Carter and Smith, 2006). The band condition around vertical axis of frequency represents near-misses, which have potential to cause serious consequence but fortunately no injuries (severity is almost 0) arises. However, as the circumstances surrounding incident categories are similar, near-misses and minor injuries appear to be of limited use in predicting more serious injuries (Marsh and Kendrick, 2000).

An alternative approach to distinguishing states on construction sites is to utilize the interrelationships between normal incidents, near-misses and accidents instead of their causation. Since 48% of damages are caused by collisions (Pratt et al., 2001) between labor, materials and plants, this approach extracts information from workers' traveling (Teizer et al., 2008). Much of the travel of construction workers is concentrated on moving around the site from one activity to another on walk-paths. From a safety management perspective, therefore, successfully monitoring the walk-path movements of workers provides a significant contribution, especially when technological aids such as RTLS are available.

One of the key challenges in applying RTLS for this purpose is in constructing a reconfigurable rule base to transform the walk-path into incidents then to states. Simple incidents known as the direct observations are built on binary operated rules, including stepping into/out of specific regions, etc., while complex incidents such as issuing a warning or drawing a response are built on simple or other complex ones by a logical operator (Hu et al., 2014), with rule based project progress being integrated with probabilistic reasoning to estimate the probability of project/worker states. However, the relationship between the walk-path and incidents has not yet been taken into consideration in real time, and it is difficult to

modify or make a decision when the scale and frequency of data increases. Only by classifying a database containing massive data into separate stored spaces, can the information needed be effectively managed and correlated.

This study aims to process the hazardous states on construction sites through mathematical models based on RTLS records to address the research gap that few researchers have developed prediction models by stochastic analysis based on historical location datasets (Zhou et al., 2013). For this, a monitoring method is developed based on RTLS and capable of predicting project and onsite worker states to provide managers with a more practical and convenient method of implementing RTLS by using a matrix-based stochastic time-series mathematical model suitable for modern complex construction safety management. To achieve this goal, necessary objectives are established:

- Define and classify the hazardous regions and states based on RTLS.
- Formulate the state transition as a stochastic process.
- Simulate and process the hazardous states.

Helmets integrated with sensors designed to capture the location are used to gather the initial data from which walk-path sources are derived. The helmet safety system allows managers to easily control and inspect the system during construction work. BLE is the chosen communication network technology, which can operate for a year without battery replacement and has an accurate communication rate (Omre and Keeping, 2010). The collected data are directly recognized as incidents, which are turned into states in the following steps according to the identified algorithms. Accordingly, a new and feasible approach to process hazardous states on construction sites is proposed, offering a useful reference for future safety management. The scope and applicability of monitoring process from a stochastic perspective clearly indicates that accidents could be addressed with the development of a variety of techniques and algorithms, which assists the managers in proactively preventing accidents. The paper presents details of the methodology, case study and results of testing the use of the Discrete Time Markov Chain (DTMC) algorithm in predicting state sequences. A sequential architecture of system monitoring is designed to construct different levels of incidents. A state recognition and transition equation and a DTMC-based model is then developed for prediction and applied in a case study. Finally, a discussion of the feasibility of using RTLS and DTMC in this application is provided to allow conclusions to be drawn.

2. Accident causation models, near-misses and the Hidden Markov Model

The most frequent causes of accidental death and injuries on construction sites are from falls, falling objects and collapses, electrical accidents and the operation of mobile plant (Wu et al., 2010b), and existing studies focus on identifying, analyzing and modeling the causes of safety hazards and risks from an integral accident perspective (Chi et al., 2005; Hinze et al., 1998). Accident causation models can be divided into three categories: (1) models of the accident process, (2) models of human error and unsafe behavior, and (3) models of human injury mechanics (Lehto and Salvendy, 1991). These models fundamentally differ from each other, leading to significantly different inputs, outputs and areas of application. The inputs include narratives, definitions and specifications. The outputs cover hazards, errors, probabilities, causes or solutions. Almost all models explicitly consider the role of human, product, task and accident processes, without a quantitative mathematical or logical structure. Models can be applied

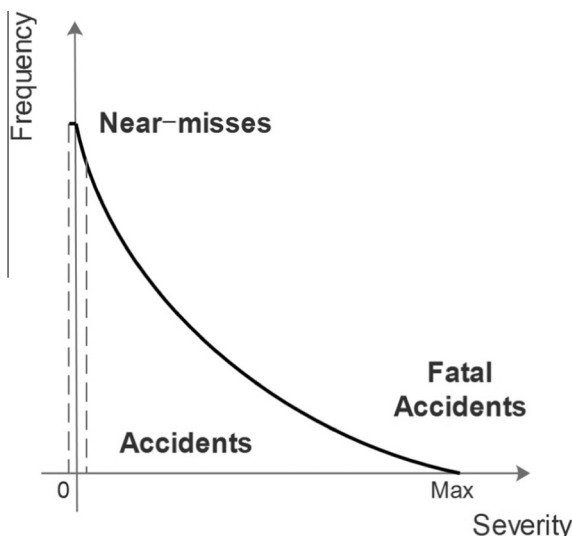


Fig. 1. Accident frequency-severity relation trend line.

quantitatively to predict hazards only when parameters are clearly specified and are limited to specific problems. To model a wide variety of behaviors, a Manual Control System can be applied to assess the deviation between actual and desired states (Rouse, 1980). If the time-lag for an effective response is too long, however, the safety system model will fail to prevent accidents within acceptable bounds.

According to the ubiquitous accident pyramid (Heinrich et al., 1950), fatal accidents occur as a result of sequences that begin from the large number of near-misses and minor-injury accidents (Lu and Li, 2009); represented the left section under curve as presented in Fig. 1. This theory recognizes that injuries could be prevented by removing factors from the sequence. If numeric estimates are attached to the consequence of incidents, the criticality of the sequences can be statically evaluated. Early safety behavioral research by Flanagan (1959) focuses on the analysis of near-misses to identify potential causes of accidents. The approach identifies forms of behaviors, which both contribute to near-misses and prevent the accident occurring, as well as emphasizing the need to effectively organize and analyze behavioral information in a timely and meaningful way.

In response, researchers in manufacturing industries have developed real-time discrete-event-based monitoring systems for radio-frequency identification-enabled shop-floor monitoring using a Hidden Markov Model. The use of rigorous mathematical models has been applied within this context to effectively predict belief states and detect disturbances (Hu et al., 2014). This suits the big-data environments of modern complex manufacturing systems and can help engineers or managers' monitor incidents and processes more effectively than traditional methods.

3. Location tracking techniques

Recently, a wide range of techniques has been considered in an attempt to effectively track and monitor construction materials and personnel. As a new technology, RFID tags have been used to monitor materials, allowing scanners to read the location at pre-identified gates or even from discrete formulations (Simic and Sastry, 2002; Song et al., 2006). Although RFID scanning is an effective way of tracking materials, this technique on its own has been ineffective in tracking worker location in real-time (Teizer et al., 2013). In response to this problem, a proactive construction management system (PCMS) was recently developed using chirp-spread-spectrum-based real-time location technology to provide feedback and post-event analysis (Li et al., 2015). Similarly, other research has developed a GPS-based antenna and bidirectional communication system of personnel to alert workers of their proximity to hazardous equipment (Abderrahim et al., 2005). However, these systems have limited tracking accuracy and have demonstrated a better outdoor than indoor performance, constraining their use in complex construction site layouts. UWB is another technique that is used in innovative and pro-active systems for automated collision detection avoidance, warning and alerts, with demonstrated higher positioning accuracy in large open space environments (Cheng et al., 2011). Research has also focused on computing algorithm development for tracking dynamic locations in real time with video cameras (Teizer and Vela, 2009).

An alternative adopted here is the use of 2.4 GHz BLE. This has several advantages in terms of customized optimization and potential improved positioning accuracy in comparison to existing techniques such as Wi-Fi, ZigBee and Classic Bluetooth. Additionally low-power operated, low-weight tags that can be hidden inside site helmets without obstruction and, most significantly, should be suitable for wearable devices (Gomez et al., 2012; Omre and Keeping, 2010).

4. Procedure for recognizing states

A dynamic systems model of state transition is used for monitoring discrete incidents. This systems model is based on a Markov Chain, wherein all states are not directly observable. In comparison to the use of a Bayesian network for classifying injury narratives (Lehto et al., 2009; Taylor et al., 2014), DTMC is a simpler modeling method and has been demonstrated to be more effective in real-time (Ross, 2014). The rigorous mathematical analysis of system state monitoring allows the study and prediction of state sequences on construction sites.

The architecture of the DTMC monitoring system, the flow of walk-path data and the database associated with multiple-level incidents is illustrated in Fig. 2. An incident processing module comprising duration filters and frequency filters is used in the monitoring system to extract useful information and construct complex incidents. In the module, a walk-path filter is firstly applied to smooth the path data from the initial land boundary and path coordinate information, removing noise, random variations and other inaccuracies. This is followed by two other filters and an algorithm that constructs complex incidents from incidents historically stored in the project database. The complete real-time information is stored in the incident database and is sourced by the monitoring module to construct the state sequences. At the end of the architecture, the DTMC module abstracts historical data from the incident database and calculates the corresponding parameters for the construction of a discrete time series. The methodologies used for predicting state sequences are based on rigorous stochastic formulations and follow the steps shown in Fig. 2.

4.1. Data collection and initial path filter

Walk-path data and sensor signals of helmet wear are collected from construction projects in real-time. Here walk-data (known as location data) is measured by a central reader detecting the worker with a peripheral tag within its range. The delivery message includes the position $r(x,y)$, timestamp t and a unique tag identification e as personal information. Here x and y denote the distances from agent to the artificial origin horizontally and vertically. Meanwhile the sensor signals are recorded by hidden sensors placed inside helmets thus, if the worker is not wearing a helmet on sites, a high level signal is sent to controller for processing by BLE and vice versa. Basically, the controller can obtain information at any time through mobile termination with the operating systems. After processing, simple incidents are identified and tracked with a Boolean variable, i.e. 0 and 1.

Sensors are hidden inside the helmets where head movement is regular, which can affect information transmission, especially with high-rise construction work. In response to RTLS data noise, with occasional outliers due to head movement, the BLE signals need to be filtered with a computation algorithm called a Robust Kalman filter (Greg and Gary, 1995; Kalman, 1960). To smooth the signals, the filter rejects outliers that would lead to errors on the walk-path curves. Through the rapid computation algorithm, a smooth path is created in real time (Harvey, 1990; Katharina, 2005).

By combining the above data and signals, it is possible to obtain real-time information of an occurrence and its location, from which simple incidents can be constructed.

4.2. Pre-analysis

The direct information collected from sensors may contains noises and has to be processed prior to becoming an incident that concerns managers, and thus to be reconstructed as formal format based on user definitions. Therefore, the messages need to be

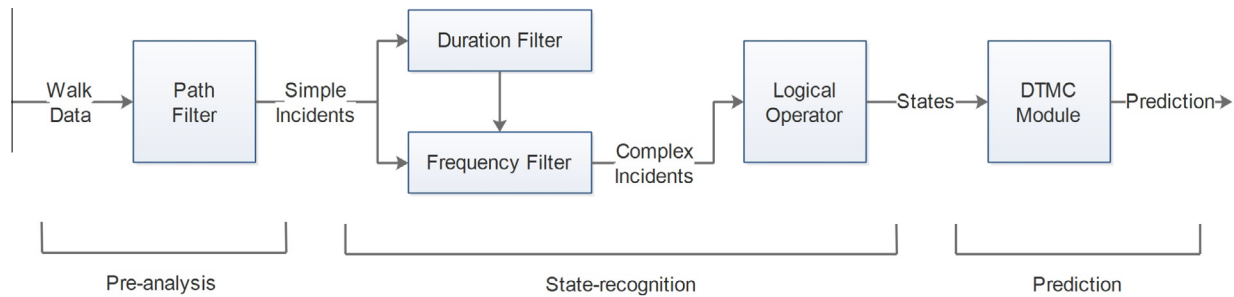


Fig. 2. Architecture of DTMC system.

pre-analyzed, which involves computation or functions to remove duplicated data, accumulating data over time intervals and classifying information for use. The pre-analysis of incident information provides clarity in recognizing information and the most directly observable behavior of the workers.

Basic incidents form the major part of the process, such as the entrance of a BLE on a work site at time t and a complete incident as a BLE exits the site. The information collected includes Boolean variables associated with a basic behavior state, as well as data for simple incidents derived from tracking the worker's location, i.e. the entrance to and exit from a marked region. The focus is on discrete incidents, such as the start and finish of construction processes, and arrival and departure from locations. The discrete time index is denoted by N . For basic incidents, are used to represent the procedures.

4.3. Recognition of key regions

After processing basic incidents from the collected information, complex incidents can then be defined. By using rules based on logical operators and sequence, the defined hazardous region distribution can reduce cost and increase productivity (Soltani and Fernando, 2004). In hazard zone modeling, incidents are determined using an attribute hierarchy. Hazard zones differ from each other according to the presence of site objects and positions. According to the degree of risk and dimension involved, dangerous regions are divided approximately into three levels that vary in terms of their probability of being inside or outside the hazard zones or safety areas surrounding the targets. The extent of the hazard zone from the object's boundary is defined by the categories of 'hazardous', 'risky', 'admonitory' and 'safe'. 'Hazardous' regions are dangerous regions such as large ditches where workers can sustain serious injury if they fell, while 'risky' regions are regions where there is a possible danger, such as under scaffolding with potential safety risks from falling objects or collapse. To allow workers to respond to dangers, 'admonitory' regions are set regions around identified hazards (Soltani and Fernando, 2004). Regions without any danger are defined as 'safe'. The distribution of the hazard zones across the construction site is represented by the following heuristics.

Certain static hazard are widely distributed on construction sites, where the hazardous area has a permanent position with fixed admonitory zones as described in Fig. 3(a), with a certainty that workers would be in danger if the areas were entered. A typical example occurs when a ditch is being excavated, the boundary of the ditch defines the hazardous zone and the extent of the exposed edges as the admonitory region. Usually a fence located between the safe and warning regions prevents workers from becoming too close to the ditch. The hazardous region of the ditch is surrounded by a safe area, with static hazards being located inside the boundary. Another example is working on scaffolding, which has a limited safe region. When workers walk outside or

close to the boundary of the scaffold, they are given a warning to prevent falling. As Fig. 3(b) shows, most falls from ladders, scaffolds, roofs and structures are of this kind. Hence, the core regions of the ladders scaffolds, roofs and structures are marked as safe regions and band regions along edges are admonitory regions. In addition, the rest regions without platforms or supports are regarded as hazardous regions.

Uncertain static hazards are areas where the objects are located permanently on a construction site without certainty of harm to the workers inside. That is, when workers step inside this area, there is a possibility of being hurt. The possibility of being struck by objects or projectiles is one example of this category and applies to most accidents, since workers have a tendency to choose a convenient but possibly dangerous way of working rather than one that is safe but inconvenient. Therefore, this distribution is often ignored by users and the circumscription between risky and admonitory regions is fuzzy in comparison with a static certain hazard distribution and can only be determined by experience. As Fig. 3(c) indicates, minor injuries or trips caused by stepping on nails or wedges, or electrocution by touching exposed wires are all potential static construction site hazards.

Uncertain dynamic hazards represent another kind of hazard involving movement. Thus, even if workers avoid fixed hazard areas and stationary, it is still possible to be injured or experience a near-miss from collisions. As vehicles, cranes and equipment move, workers can be accidentally injured by falls and collisions. Since both workers and the hazards are moving, the maximum effective area boundary within a fixed distance is utilized to construct dynamic uncertain hazard areas. For example, as a tower crane produces moving hazard zones under its boom while lifting or slewing in a circle, moving vehicles occupy the ribbon illustrated in Fig. 3(d).

4.4. Recognition of incidents

After establishing the hazardous areas, an incident recognition algorithm is integrated into the monitoring system for automatically classifying incidents. Basic incidents are tracked by the BLE. However, it is only through the recognition of incidents that the system can filter them in terms of complexity. Additional observables are user commands, actions or documents. Considering the significant sensitivity of wave signals by BLE, the monitoring system is highly sensitive – resulting in potential misreads of walk-paths. Therefore, duration and frequency limitation is needed to eliminate errors. To do this, the duration of workers in different regions are computed by recording their entrance and exit times. The algorithm proposes a time-bounded limitation consisting of categories during a prescribed period. The maximum duration time is denoted by T_{limit}^{+} for excluding work that has to be completed in dangerous areas. The minimum duration time T_{limit}^{-} aims to remove information errors so that users can obtain sufficiently accurate

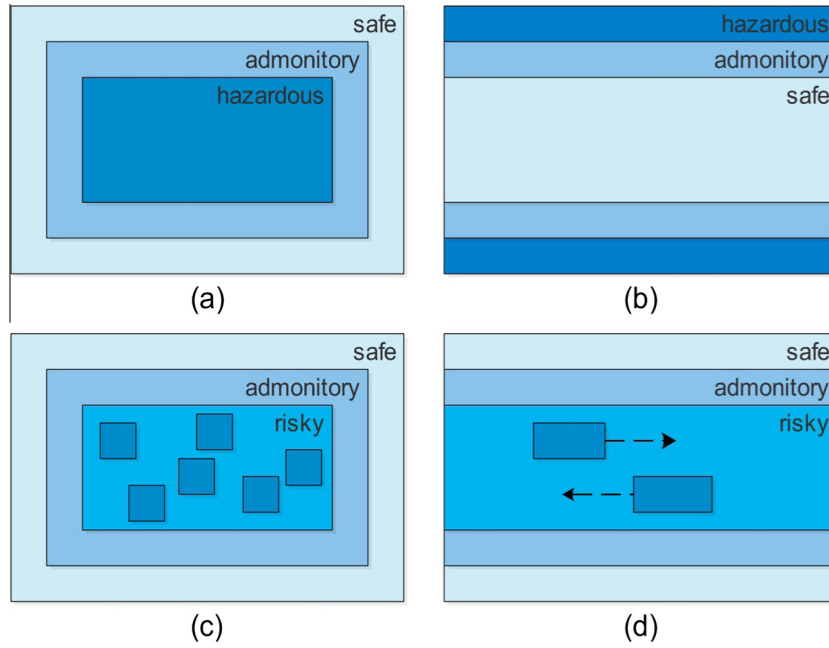


Fig. 3. Distribution and categories of hazardous regions.

walk-path data. The influence of duration can be expressed as a mathematical function

$$f_t(t) = \begin{cases} 0 & \text{if } t < T_{limit}^- \\ \frac{T_{limit}^+ - T_{limit}^-}{2} \times \left| \frac{T_{limit}^+ + T_{limit}^-}{2} - t \right| & \text{if } T_{limit}^- \leq t \leq T_{limit}^+ \\ 0 & \text{if } t > T_{limit}^+ \end{cases} \quad (1)$$

where t is the duration time the user remains in the marked zones and $f_t(t)$ is the duration discriminant of the worker's behavior. The duration value can be used to continuously modify the time limitation and therefore $f_t(t)$ can be used to estimate the hazard.

A frequency limitation is also applied to complete the algorithm. Termed N_{limit} , this is used to remove cases such as a worker stepping into a ditch during earthworks. The piecewise function below describes the frequency filter as:

$$f_N(n) = \begin{cases} 1 - \frac{N_{limit} - n}{N_{limit}} & \text{if } n \leq N_{limit} \\ 0 & \text{if } n > N_{limit} \end{cases} \quad (2)$$

where n , a positive integer, is the number of times that a worker steps into a special region.

Calculating the duration and frequency of incidents enhances the accuracy of the walk-path and identifies user incidents that occur occasionally, deliberately or because of communication errors.

4.5. Recognition of states

To monitor process effectively, the discrete statistical computation of the states on a construction site is used. As the states of the project or workers are not directly observable, the RTLS data is collected and analyzed at time intervals, where each state corresponds with special incidents occurring each day. Assumptions are made to divide safety performance temporarily into four states according to the frequency of incidents. As Table 1 shows, the states and incidents observed are recorded on an interrelated map. N with corner marks are practical thresholds based on experiences, that small thresholds leading to sensitive warning systems and vice versa.

The monitoring system is modeled in terms of states, which are obtained from the statistical result of the RTLS recorded worker path during each day of construction. The algorithm divides the statistical computation from two views according to the severity rate involved. If a worker receives no warnings and avoids hazardous regions, the system registers a *normal state*. However, if a warning alert is recorded more than once, the mode changes to an *incidence state*, drawing the attention of site management. Both *near-miss* and *accident states* are classified by injury level and project impact from the RTLS data. Generally, the near-miss state relates to potential minor injuries associated with uncertain hazardous areas while the accident state relates to grievous or fatal injuries associated with certain or uncertain hazardous regions.

From the overall project view, the critical value is estimated according to the specific site states. In consideration of a lower fault-tolerance in construction projects, the algorithm expands the limitation compared with the individual view. Thus, the normal project state involves restricting the frequency of workers entering admonitory regions with a warning, which is denoted by N_{A1} . The incident state can include incidents such as entering hazardous regions N_{H1} times without injury but which may cause project disruption. A near-miss state represents hazardous incidents between N_{H1} and N_{H2} , which may also lead to project disruption. Finally, the accident state represents more than N_{H2} accident incidents including critical injury events.

The four identified states define daily worker safety performance. Since walk-paths randomly extend over a construction site, the walk-path states are predicted according to a random probability distribution or stochastic.

5. Modeling system for state monitoring

Since the accidents on construction sites are results of a variety of causations, therefore state sequence identified before could be regarded as a stochastic process. To monitor the process, DTMC is proved to be a feasible solution in manufacturing industry (Hu et al., 2014). Markov-type models requires no deep insight into the mechanisms of dynamics, however it could indicate states as a guide and simulation of future, which is also relatively easy to

Table 1
State recognition from incident frequency.

	Symbols	States	Frequency of incidents			Influences
			Safe	Admonitory	Hazardous	
Personal State	S1	Normal	$(0, +\infty)$	–	–	–
	S2	Incidence	$[0, +\infty)$	$(0, +\infty)$	–	Shock
	S3	Near-miss	$[0, +\infty)$	$(0, +\infty)$	$(0, +\infty)$	Minor Injuries/Shock
	S4	Accidents	$[0, +\infty)$	$(0, +\infty)$	$(0, +\infty)$	Grievous/Fatal Injuries
Project State	S1	Normal	$(0, +\infty)$	$[0, N_{A1})$	–	–
	S2	Incidence	$[0, +\infty)$	$[N_{A1}, N_{A2})$	$[0, N_{H1})$	Disturbances
	S3	Near-miss	$[0, +\infty)$	$[N_{A2}, +\infty)$	$[N_{H1}, N_{H2})$	Suspension
	S4	Accidents	$[0, +\infty)$	$(0, +\infty)$	$[N_{H2}, +\infty)$ or $[1, +\infty)$ Fatal Event	Stand-down

infer from small number of historical state by simple calculation (Deng et al., 2015; Von Hilgers and Langville, 2006). Just like the hypothesis of DTMC, the project process operates without a long-term memory, and once an accident has occurred, the likelihood of the same accident type occurring again the following day is low due to the use of increased project warnings and prevention measures. Since the Markov property is also fit for construction industry, the state sequence model assumes that the future state is influenced by the present state, but independent of the past state. Moreover, the model assumes the transition from state to state as an unchanging variable to simplify the sequence. Thus, the states of accidents are constant, even if an on-site worker experience increases or physical function decreases.

5.1. State transition

The set of four distinct states, comprising normal, incidence, near-miss and accident states, are respectively denoted as S1, S2, S3 and S4. The system contains a transition matrix according to the regular minimum discrete time intervals. The matrix consists of probabilities associated with the circumstances between states and state transitions. Additionally, the state transitions and their interrelationships differ from two views: individual workers and the overall project.

As the cause of an accident is difficult to measure and analyze, a stochastic model is used to analyze the states. Although it is possible to identify the time and severity of an accident from historical data, the labor and project states have no certain causality consequences. According to the proposed transition matrix, every probabilistic state is derived from a pre-processor state except the current and predecessor state. This relationship can be expressed as a mathematical function:

$$P(X_{t+1} = x_{t+1} | X_1 = x_1, X_2 = x_2, \dots, X_t = x_t) = P(X_{t+1} = x_{t+1} | X_t = x_t) \quad (3)$$

where time corresponds to the state changes as $t = 1, 2, 3, \dots$, and the actual state at time t is denoted by X_t . To estimate the active states, $\gamma_{ij}(u)$ denotes the probability of a transition from state S_i to S_j during the period u , as a data-driven parameter from historical RTLS records

$$\gamma_{ij}(u) = P(X_{t+u} = S_j | X_t = S_i) \quad i, j = 1, 2, 3, 4 \quad (4)$$

Suppose Γ is the matrix of state transition probabilities consisting of γ_{ij} , whose period is identified to be one day. Then, the transition matrix of the four states is expressed as

$$\Gamma = \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{14} \\ \vdots & \ddots & \vdots \\ \gamma_{41} & \cdots & \gamma_{44} \end{bmatrix} \quad (5)$$

where the diagonal entries γ_{ii} represent the probabilities of remaining in the same state and all entries are positive. Since the probabilities obey standard stochastic constraints and come from the frequency of state occurrence, $\sum_{j=1}^4 \gamma_{ij}$ of each row is equals to 1.

The transition matrix has different variable values depending on the recognition performance. From the project view, managers focus on minimizing the disruption to project activities, even if accidents have occurred. The transition matrix of this recognition is illustrated in Fig. 4(a). However, from individual worker's view, an injured worker would not continue working following a major accident. Thus, the model will result in a stationary distribution at an accident state. As Fig. 4(b) shows, the mapping between normal, incidence, near-miss and accident states is unidirectional, while the related coefficients are zero.

5.2. Hidden interrelationship between observation and invisibility

As most construction site records only capture major accidents, such as grievous or fatal injuries, it is difficult for managers to keep track of safety incidents from past projects. The increased uptake of automated technology and techniques on construction sites has resulted in the capture of a large amount of process data, which can aid project decision-making. By drawing on the interrelated network of observable and invisible data, the state prediction accuracy can be improved without losing any related information.

As Fig. 5 shows, the statistical output produced by the RTLS is dependent on observable data analysis. The modeled stochastic incidents within hidden states reveal interrelationships between the frequency and duration of incidents, the severity of accidents and the other interactions between workers and hazards. The incidents include normal tasks, warning alerts and the nature of accidents, which all pass through the recognition algorithm for processing.

As Fig. 6 illustrates, the Markov Chain is invisible and thus the observer can determine the current state from the information offered by the RTLS. The random variable X_t is the actual hidden state at time t , and Y_t is the observations of entering the hazardous regions. The arrows in the diagram denote conditional dependencies. This demonstrates that the conditional probability distribution of the hidden variables depends only on the value of the hidden variable X_{t-1} , as the prior values have no influence as defined by the Markov Chain. The probability of the state is determined by its definition and on the frequency of incidents. Similarly, if the model can predict future state sequences, it can also simultaneously predict the value of the observed variable Y_t depending on the value of the hidden variable X_t

$$p_i(y) = P(Y_t = y | X_t = S_i) \quad i = 1, 2, 3, 4 \quad (6)$$

where $p_i(y)$ denotes the probability of visible variables under the state S_i . To simplify computation, the function assumes $P(y)$ is the

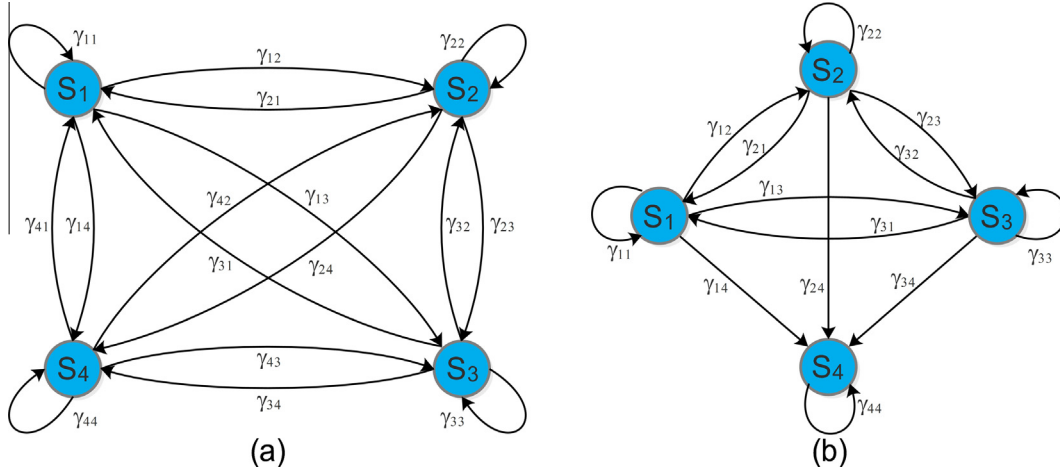


Fig. 4. State transition diagram.

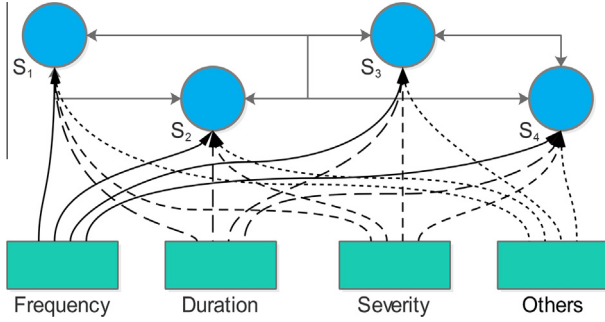


Fig. 5. Interrelationship between states and observations.

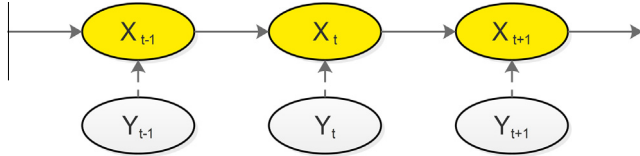


Fig. 6. Time series of observations and invisibilities.

matrix of interrelated transition, where diagonal entries are defined as $p_i(y)$ and the rest position is zero.

$$P(y) = \begin{bmatrix} p_1(y) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & p_4(y) \end{bmatrix} \quad (7)$$

This probability function can be used to estimate the expectation of incidents per interval, on the condition that the initial state is already known through history or provided by domain experts. Assuming that workers commence work from their first day on a construction site until the end of a project, the situation is defined from normal, incidence, near-miss and accident states. As denoted previously, X_t represents the state on the day t , with X_0 as the initialization, followed by the Discrete-Time Markov Chain sequence.

$$q_i = P(X_0 = S_i) \quad i = 1, 2, 3, 4 \quad (8)$$

where q_i denotes the probability of the initial states. Therefore, the frequency, duration and severity of incidents can be expressed as vectors using the recognition rules above, denoted by Y_t . On the

condition that the process is initialized based on the preceding definition, the probability of the observation y is

$$P(Y_t) = [q_1, q_2, q_3, q_4] \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{14} \\ \vdots & \ddots & \vdots \\ \gamma_{41} & \cdots & \gamma_{44} \end{bmatrix}^{t-1} \begin{bmatrix} p_1(y) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & p_4(y) \end{bmatrix} \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} = QI^{t-1}P(y)\mathbf{1}' \quad (9)$$

where $P(Y_t)$ is the probability of monitoring Y_t on day t , based on a constant transition matrix and Q denotes the initial probability vector of states that can be monitored from the beginning of the project.

In recognition of the definition above, the two parameters are defined from two views, namely transition probability and emission probability. As all four states are possible each day and any one transition probability can be determined when other probabilities are known, there are at least a total of 12 transition and 4 emission parameters for each view. In an actual project, historical records can produce the transition matrix from an analysis of event likelihood and experience, strengthening the validity of data in comparison to artificially determining the states.

6. Case study and result

A construction project case study is used to illustrate the application of the DTMC model. In this case, it is assumed that the site managers employ the algorithm without modeling accident causation. The following describes the monitoring functionality of states based on the RTLS and admonitory observations.

6.1. Incident monitoring

The site managers tracked the walk-path and warning information of nine experienced workers and the hazardous regions on a construction site at weekly intervals. This involves five steel fixers, two concrete operators, a carpenter and a welder. Each worker wore a helmet with the sensors and RTLS tags. Once the work process commenced, the workers were electronically logged into the monitoring system with their related information by scanning the RFID tags, allowing the managers to monitor activity in real-time. The monitoring system recorded the path, timestamp, and assessed whether the coordinates of moving objects were within hazardous or admonitory areas with a real-time frequency of

5 Hz. The rule recognition and pre-analysis data were then processed by the filter, which extracted simple incidents and smooth walk-paths for further analysis.

To calibrate the system, the N_{limit} values were initially set quite high and the frequency of a single worker, tasked with the placing of reinforcement, entering admonitory and hazardous regions was closely recorded as shown in Table 2. The recorded regions included the foundation ditch and areas under the crane boom. The N_{limit} values were then gradually lowered to more accurately represent the region state, with the frequency of the normal state being dropped to near zero when no warnings were recorded over a daily period.

From the project view, the observations of the nine workers were summarized for further analysis. The managers then established critical values based on the project's fault tolerance. This resulted in frequency limitations of 225 and 25 respectively. Thus, if the workers' entered any admonitory or hazardous region over 225 or 25 times respectively, the daily state was automatically categorized as 'admonitory' or 'near-miss' as a minimum.

Table 2 presents the results of the case study, where there were no injuries and only includes uncertain hazardous regions. The case focuses on the frequency of alerts. Detailed statements explaining the distribution of the warnings, the extent of worker tasks and project processes per day may also be included. Currently, the algorithm analyzes the frequency, duration and severity of incidents. By utilizing basic figures instead of complex incidents, the monitoring system can tolerate more information in a big-data environment.

6.2. State monitoring

According to the Hong Kong Housing Authority, the Hong Kong construction industry accident rate was 40.8 per 1000 workers and recorded 22 fatal accidents among 3232 incidents in 2013 (Hong Kong Housing Authority, 2015), which means the statistical probability of state 'accidents' (S4) is 0.0408 and the sum of the left three states' probabilities is 0.9592. Meanwhile the case results indicate the proportion of normal, incidences and near-miss states is 4:2:1. Since the frequency of warning incidents is far greater than near-misses and accidents, ignoring the low accident rate, the probabilities of 'normal', 'incidences' and 'near-misses' states could be assessed by dividing 0.9592 in perspective. Thereafter, the initially estimated four-state proportions are:

$$Q = [q_1, q_2, q_3, q_4] = [0.5481, 0.2741, 0.1370, 0.0408] \quad (10)$$

To satisfy the needs of actual construction processes, managers are encouraged to predict states based on current situations and draw upon historical records to improve accuracy and computational efficiency. In this case, the control simulated state sequence using a Monte Carlo method from the project view was conducted involving up to 10,000 iterations based on the proportions in (10). Accumulated counting was used to derive the transfer probability needed to calculate the one-step transition from state to state, which is a component of the transition matrix

$$\Gamma = \begin{bmatrix} 0.5488 & 0.2747 & 0.1401 & 0.0364 \\ 0.5419 & 0.2805 & 0.1439 & 0.0337 \\ 0.5395 & 0.2722 & 0.1446 & 0.0437 \\ 0.5225 & 0.2732 & 0.1406 & 0.0637 \end{bmatrix} \quad (11)$$

With the transition matrix and the initial distribution of states established, the algorithm operates within a stochastic prediction of state sequence. Fig. 7(a) shows the results of the simulations, where the upper state is the tentative basic sequence selected from the first 250 days; the middle is the predicted state sequence from the DTMC model; and the bottom state is the combined frequency of the normal and incidence states. Table 3 summarizes the comparative frequencies involved, based on the first 250 and 1000 days, indicating that the DTMC predictor decreases the possibility of accident states while controlling the prediction for normal and incidence states. The results show the maximum and minimum relative deviations between the two state sequences is 64% and 4% respectively when the prediction time is short. For long-term prediction, stability decreases, while the estimation of the accident state increases. Despite this, the relative deviation ranges from 10% to 17%, which is expected to be improved in future research to increase predictive power and robustness.

Compared with the simulated state sequence completed by Monte Carlo method, the predicted state sequence completed by DTMC contains more normal states in both short-term and long-term that may be the result of the different sensitivities of the two methods. State transition parameter matrix of DTMC is derived from the updating data, summarizing the essential changes between states, leading to heighten sensitivity over the dynamic process. It seems to be more realistic that accidents will decrease with the development of protective equipment and management. Meanwhile computational requirements of both methods are modest and achievable. Therefore DTMC is relatively efficiency to extract from time series sequences rather than Monte Carlo. Moreover, the simulation carried out without deep insights into the mechanisms of the accident causations, yet indicates state sequences and hence performs as a guide to promote.

The number of states per week was also analyzed. The top sequence row in Fig. 7(b) shows the initial sequence, followed by the prediction in the middle sequence row and the control simulated sequence in the bottom row. The width of the lines represents normal, incidence, near-miss and accident states in fine to heavy lines respectively. The comparative line chart illustrates the difficulty for the algorithm to predict the state on an exact marked day. Although the frequency trends are in the same direction of the long-term distribution, it demonstrates the need for future research to improve performance.

Since the simulated case is static, the state sequences do not change over time. However, on a construction site, the accident rate would generally decrease with the development of applied techniques to prevent further accidents, suggesting the transition matrix would change after a new state is added in the sequence each day. The research indicates the monitoring system is feasible in accident state detection and effective in real-time to enable managers to respond promptly to such disruptions during construction.

Table 2
Monitoring incidents variables.

Time		1st week	2nd week	3rd week	4th week	5th week	6th week	7th week
Personal States	Admonitory	23	11	20	3	9	3	18
	Hazardous	0	4	6	0	3	6	0
	States	S2	S3	S3	S2	S3	S3	S2
Project States	Admonitory	220	205	319	93	197	242	267
	Hazardous	0	7	23	2	8	18	9
	States	S1	S1	S3	S1	S1	S2	S2

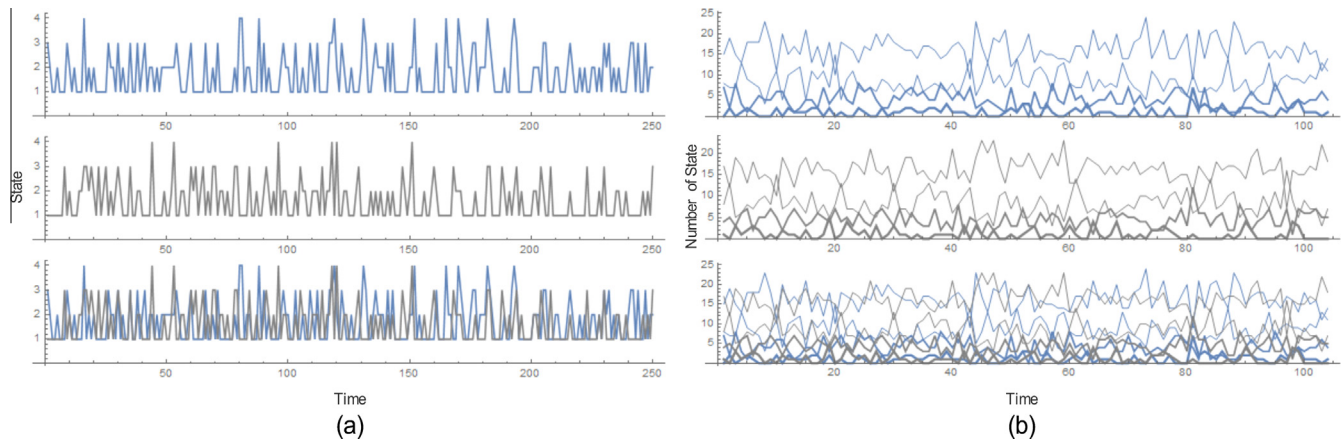


Fig. 7. Comparison of simulated and predicted state sequence.

Table 3
Comparison of simulated and predicted state frequency.

States	S1	S2	S3	S4
Simulated state sequence (250)	128	77	34	11
Predicted state sequence (250)	134 (+6,+4%)	81 (+4,+5%)	31 (−3,−9%)	4 (−7,−64%)
Simulated state sequence (1000)	500	304	150	46
Predicted state sequence (1000)	552 (+52,+10%)	281 (−23,−8%)	129 (−21,−14%)	38 (−8,−17%)

7. Conclusion

This paper presents a stochastic state sequence mathematic model for accident prediction in a BLE-enabled construction site using RTLS data. Algorithms are designed to predict hazardous regions, incidents and states to be monitored from both individual and project views. The algorithms are based on critical values to allow users to easily modify state definitions pending additional information from historical records and actual situations. Additionally, a DTMC model is developed, based on the hidden interrelationship between site observations and invisibilities, to predict possible states on a construction site and dynamically detect disruption. Finally, a case study is presented to demonstrate the feasibility of the developed method.

Future research needs to focus on improving the accuracy of the method with less reliance on historical data and further define the strict interrelationships between the observations and hidden states. This will allow greater predictive power from the actual state sequence, such as the frequency of warnings. Additionally, the system needs to empirically tested on future construction sites to collect interrelated event information including frequency, duration and severity. In light of the positive influence of pro-activities in preventing accidents and post-activities in decreasing accident severity, more functions need to be integrated to further optimize the process and enable a more detailed analysis of real-time cases. Therefore, the model can be customized for specific construction projects and the workers involved. Currently, the prediction method is primarily suited to the big-data environment of construction projects. However, with future improvements, it could be adapted to other project contexts and improving the integration of information derived from new data collection and prediction techniques.

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