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A dynamic Bayesian network based approach to safety decision support in tunnel construction

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ABSTRACT

This paper presents a systemic decision approach with step-by-step procedures based on dynamic Bayesian network (DBN), aiming to provide guidelines for dynamic safety analysis of the tunnel-induced road surface damage over time. The proposed DBN-based approach can accurately illustrate the dynamic and updated feature of geological, design and mechanical variables as the construction progress evolves, in order to overcome deficiencies of traditional fault analysis methods. Adopting the predictive, sensitivity and diagnostic analysis techniques in the DBN inference, this approach is able to perform feed-forward, concurrent and back-forward control respectively on a quantitative basis, and provide real-time support before and after an accident. A case study in relating to dynamic safety analysis in the construction of Wuhan Yangtze Metro Tunnel in China is used to verify the feasibility of the proposed approach, as well as its application potential. The relationships between the DBN-based and BN-based approaches are further discussed according to analysis results. The proposed approach can be used as a decision tool to provide support for safety analysis in tunnel construction, and thus increase the likelihood of a successful project in a dynamic project environment.

1. Introduction

Underground transportation systems are in great demand in many large cities all over the world. The engineering design and construction of railway tunnels below ground have been one of the favorable options in urban transport development. In the past ten years, tunnel construction has presented a powerful momentum for rapid economic development worldwide. However, owing to various risk factors in complex project environments, safety violations occur frequently in tunnel construction, leading to large problems on the surface transport operation. On July 6, 2010, a tunnel collapse took place in Prague, Czech Republic, causing a 15-meter-wide sunken pit to surface on the above road [1]. On August 23, 2012, a metro line leak caused chaos in Warsaw, Poland. Water flooded into the tunnel at the planned Powisle station, causing considerable transportation problems in the already gridlocked city [2]. In China, the number of construction accidents showed a rising trend in tunnel projects. On November 15, 2008, a fatal tunnel collapse incident occurred a year after the start of Metro Line One in Hanzhou Metro Construction, resulting in the deaths of 21 people. The affected section by the collapse was 100 m long by 50 m wide, and the depth of the crater was given as 6 m [3]. In general, there steps up a public concern that tunnel construction can generate ground displacements and deformations [4,5], which may affect the safety performance of surface buildings and road operations, and lead to unacceptable damages.

To avoid heavy casualties and property losses caused by safety violations, innumerable studies have introduced risk-based analysis into safety control. Risk analysis can be divided into qualitative and quantitative risk analysis [6]. The former includes Fault Tree Analysis (FTA), Comprehensive Fuzzy Evaluation Method (CFEM), Safety Check List (SCL) and others; while the latter includes job risk analysis method, influence diagrams, Neural Network (NN), Support Vector Machine (SVM), decision trees and others. The above risk-based analysis methods make a significant contribution to safety management in complex engineering projects [7,8], however, they are confined to static control management [9]. Khakzad and Khan [10] described FTA unsuitable for complex problems due to its limitation in explicitly representing the

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dependencies of events, updating probabilities, and coping with uncertainties. When associated parameters, such as geological, design and construction parameters were changed, the aforementioned methods could not accurately illustrate the updated feature of dynamic environments as the construction progress evolved. Nor can professional supports or suggestions be provided in real time as the parameters were updated.

In recent years, Bayesian network (BN) has been proposed to model the complexity in man-machine systems [11], and is widely used to implement uncertain knowledge representation and reasoning [12,13]. However, in conventional BN-based analysis, it is a static model representing a joint probability distribution at a fixed point or a time interval. The dependencies among the random variables are not presented when constructing the BN model, leading to possible deviations between the predicted results and those observed in reality [14]. Instead, a dynamic Bayesian network (DBN) is a long-established extension of the ordinary BN, and allows explicit modeling of changes over time. Thus, DBN can therefore model the evolution of the probabilistic dependencies within a random system. In general, use of BN and DBN in engineering applications can speed up significantly nowadays [15]. Basically, both BN and DBN allow designers to easily update the prediction when additional information is available, and are especially suitable for engineering applications, where statistical data is often sparse [14,16]. This paper therefore attempts to use the DBN techniques to address the potential uncertainty and randomness underlying the safety management in tunnel construction. A systemic decision support approach based on DBN is developed, aiming to provide guidelines for dynamic safety analysis of the tunnel-induced road surface damage over time. The proposed approach can be used to conduct various analysis tasks, including predictive, sensitivity and diagnostic analysis. Finally, a case study concerning the dynamic safety analysis in the construction of Wuhan Yangtze Metro Tunnel in China is used to verify the applicability of the proposed DBN-based approach. The relationships between the DNB-based and BN-based approaches are further discussed according to the analysis results.

This paper is organized as follows. Section 2 defines the fundamental theory of BN and DBN. In Section 3, a decision support approach with detailed step-by-step procedures is developed. In Section 4, the safety risk mechanism of the tunnel-induced road surface damage is investigated, providing a basis for the risk modeling and decision support. In Section 5, the proposed approach is applied to dynamic safety analysis in a tunnel case study. The conclusions are drawn in Section 6.

2. Methodology

2.1. Bayesian network

Bayesian network (BN), a combination of graph theory and probability theory, consists of a directed acyclic graph (DAG) and an associated joint probability distribution (JPD) [17]. A BN model with N nodes can be represented as $B<G,\Theta>$, where G stands for a DAG with N nodes, and Θ stands for the JPD of the BN model. The nodes $\{X_1,\ldots,X_N\}$ in the graph are labeled by related random variables. The direct edges between nodes present association relationships among the variables. DAG contains conditional independence assumptions, which can be modeled by means of engineering models, expert judgment, or other known relations [14]. The relations represented by DAG allow the JPD to be specified locally by the conditional probability distribution for each node. Assuming $Pa(X_i)$ is the parent node of X_i in the DAG, the conditional probability distribution of X_i is denoted by $P(X_i|Pa(X_i))$. The JPD of $P(X_1,\ldots,X_N)$ can then be written as Eq. (1). Also, BN offers advantages over alternative artificial intelligence (AI) approaches, such as NN or fuzzy logic, due to its capability of handling uncertainty in data [18]. Furthermore, BN allows not only a forward (or predictive) analysis but also a backward (diagnostic) analysis, where the posterior probability of any set of variables can be computed.

$$P(X_1,\ldots,X_N)=\prod_{X_i\in\{X_1,\ldots,X_N\}}P\left(X_i\middle|Pa(X_i)\right) \tag{1}$$

2.2. Dynamic Bayesian network

Dynamic Bayesian network (DBN) extends the ordinary BN formalism by introducing relevant temporal dependencies that capture the dynamic behaviors of domain variables between representations of the static network at different times [19,20]. Thus, DBN is more appropriate for monitoring and predicting values of random variables, and capable of representing the system state at any time with respect to BN [18]. A DBN model is a way to extend BN to model probability distributions over semi-infinite collections of random variables $\{X_1, X_2,\ldots,X_N\}$. Typically, we assume that each state only depends on the immediately preceding state (*i.e.*, the system is first-order Markov), and two time slices are considered in order to model the system temporal evolution. A DBN model represents a discredited Markov chain process, and this form of DBN is usually called 2TBN (two time-slice temporal Bayesian network) [19,21]. Accordingly, a DBN model is defined to be a pair $(B_1, B_{\rightarrow})$, where B_1 is a BN model that defines the prior $P(X_t)$, and $B_{\rightarrow}$ is a 2TBN which defines $P(X_t|X_{t-1})$ by means of a transition probability table, as seen in Eq. (2). Herein, X_t^i stands for the ith node at time t ($i=1, 2,\ldots,N$), and $Pa(X_t^i)$ stands for the parents of X_t^i in the directed acyclic graph.

$$P(X_t|X_{t-1})=\prod_{i=1}^{N}P(X_t^i|Pa(X_t^i)) \tag{2}$$

The nodes in the first slice of a 2TBN do not have any parameters associated with them, however, each node in the second slice of the 2TBN has associated a conditional probability distribution for variables which defines $\prod_{i=1}^{N}P(X_t^i\middle|Pa(X_t^i))$ for all $t>1$ [22,23]. The distribution given by a 2TBN can be divided into two aspects, namely (i) the inter-slice distribution that models the probability of variables in X_t with parents at time $t-1$; and (ii) the intra-slice distribution that models the probability of variable in X_t with parents in the same time slice [24]. Generally, we assume that the parameters of the conditional probability distribution are time-invariant, and the model is time-homogeneous. The parents of a node $Pa(X_t^i)$ can either be in the same time slice or the previous time slice [23]. The arcs between slices are from up to down, reflecting the causal flow of time. If there is an arc from X_{t-1}^i to X_t^i, this node is called persistent. The arcs within a slice are arbitrary, and one can put arcs in any way one wants to (*i.e.*, their relationships are unconstrained), as long as the intra-slice-model is acyclic. In this paper, the parameters of the conditional probability distribution used by the proposed model are assumed time-invariant. When we unroll the 2TBN until we have T time slices, the resulting joint distribution probability can be defined by Eq. (3).

$$P(X_{1:T})=\prod_{t=1}^{T}\prod_{i=1}^{N}P(X_t^i|Pa(X_t^i)) \tag{3}$$

3. Development of a DBN-based decision support approach

Aiming to improve the effectiveness and accuracy of safety management in complex project environments, a decision support