RISK IDENTIFICATION EXPERT SYSTEM FOR METRO CONSTRUCTION BASED ON BIM

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ABSTRACT

This paper presents a BIM-based Risk Identification Expert System (B-RIES) for metro construction, composed of three main built-in subsystems: BIM extraction, knowledge base management, and risk identification subsystems. The engineering parameter information related to risk factors is extracted from the BIM of a specific project where the IFC standard plays a bridge role between the BIM data and metro construction safety risks. An integrated knowledge base, consisting of fact base, rule base and case base, is established to systematize the fragmented explicit and tacit knowledge. A hybrid inference approach, with case-based reasoning and rule-based reasoning included, is developed to improve the flexibility and comprehensiveness of the system reasoning capacity. During the safety risk identification process, B-RIES is able to improve the inefficiencies in engineering information extraction, reduce the dependence on domain experts, and facilitate knowledge sharing and communication among dispersed clients and domain experts. A typical safety hazard identification in the Mingdu station, located in the Wuhan Metro Line Two, is presented in a case study. The results demonstrate the feasibility of B-RIES, and its application potential. B-RIES can be used as a decision support tool to provide guidelines for safety management in metro construction, and thus increase the likelihood of a successful project in a complex environment.

KEYWORDS

metro construction; safety risk identification; expert system; knowledge management; rule-based reasoning

INTRODUCTION

In the past ten years, metro construction has presented a powerful momentum for rapid economic development worldwide. Owing to various risk factors in complex environments, safety violations occur frequently in metro construction and bring enormous hidden dangers for the public safety (Waltz, 2012; Yu, 2012). Many safety hazards have led to the growing public concern for a priori risk assessment in relation to the metro construction safety (Abdelgawad & Fayek, 2010).

In the actual construction industry, the common practice is to expect the domain experts to identify the safety risks on a basis of engineering drawings. At first, values of risk related parameters, served as input information, are obtained by reading the engineering drawings. Then, based on the prior knowledge achieved from standards, technical reports, literatures or construction experience, the domain experts make efforts to carry out the results of hazard identification for safety assurance. However, there mainly exist three deficiencies during the current safety hazard identification approach as follow: (1) The knowledge related to hazard identification in the literatures and technical documents is not systematically organized and is mostly in a scattered and repetitive condition, which increases the difficulty for knowledge acquisition; (2) The above mentioned methods excessively rely on the domain experts due to the lack of autonomous inference capacity. Actually, the domain experts are generally considered as a scarce resource which are not able to provide universal consultation and real-time guidance because of time constraints (Cai & Xu, 2004); (3) The process of the engineering parameters information extraction involves many time-consuming and error-prone activities, especially for reading engineering drawings, which would significantly affect the accuracy and effectiveness of the final identification results (Cao, Li, & Liang, 2005).

Building Information Modelling (BIM) is considered as an emerging information technology that promotes a collaborative process for the Architectural, Engineering, Construction and Facilities Management (AECFM) industry.. Compared to the conventional two-dimensional (2D) drawings, BIM provides a more realistic and enriched model, and is beneficial to all phases in the building life cycle (Zhang, Teizer, Lee, Eastman, & Venugopal, 2013). On the other hand, the Expert Systems (ES) technique provides a powerful tool for knowledge integration and autonomous inference mechanism (Martín, León, Luque, & Monedero, 2012). ESs are designed to solve complex problems by reasoning about knowledge like an expert, which helps to significantly reduce dependence on the domain experts in actual construction practices. Combining these two techniques together provides a full solution for the aforementioned deficiencies and shortages. In this paper, a BIM-based Risk Identification Expert System (B-RIES) for metro construction is developed, mainly consisting of three built-in subsystems: BIM Extraction Subsystem, Knowledge Base Management Subsystem, and Risk Identification Subsystem. B-RIES attempts to systematize the fragmented knowledge and facilitate the knowledge sharing and communication among dispersed clients and domain experts. A typical safety hazard in the Mingdu station that is one station in the Wuhan Metro Line Two is used for a case study. The results demonstrate the feasibility of B-RIES, as well as its application potential.

RELATIONSHIPS BETWEEN BIM AND METRO CONSTRUCTION SAFETY RISKS

Metro construction is characterized as a highly complicated project with large potential risks, which integrate multiple designing disciplines, sub-projects and sub-project interfaces (Gambatese, Behm, & Rajendran, 2008). Information technology has proven to be crucial to the success of a project by effectively controlling the safety risks. Information flow from design to construction is critical and, when efficiently controlled, it allows for design-build and other integrated project delivery methods to be favored. BIM is regarded as the information carrier of engineering characteristics, structure design and structure regulations. The information concerning structural component attributes, constraint relations, the interaction of the structure and the surrounding environment, construction technical information, is all covered in a BIM model. Most metro construction safety risks are closely related to this engineering information, and thus the experienced experts and engineers can identify risks and risk factors through reading the conventional 2D engineering drawings. However, BIM itself cannot identify the potential safety risks due to the lack of inference capacity, but can provide the related information needed in the risk identification process.

The Industry Foundation Classes (IFC) standard has been developed as an open standard for common data structures on information capturing and exchange (Model, 2008). The IFC standard is supporting building elements, material, properties, geometry and placements, addressing the broad scope of building design, engineering, construction, and operation. IFC provides an extensive set of generic building object types, such as beam, column, wall, slab, etc. with associated attributes and other properties. Besides that, IFC also offers numerous shape definition methods and means to depict relations between objects. The intended role of the IFC is to depict all information associated with a building through construction, and to support exchanges of this range of information.

Integration of the open IFC standard into BIM, also called Open BIM, seeks solutions to improve the productivity and efficiency of the building process by enabling interoperability between AEC/FM and BIM software applications. From the respective of IFC-based BIM, all the building components are derived by IfcProduct entities. The IfcProduct entity stands for an abstract base class, consisting of several hundred entities organized into an object-based inheritance hierarchy. The entities aim to define the geometrical model of the building components, including the physical objects (walls, beams, panels and columns, etc.), abstract objects (relationships, types, groups, etc.), and material objects (concrete, steel, etc.). Those information are stored in open formats, making them accessible and readable for anyone, and not locked into proprietary software formats. In this way, the risk related information concerning the engineering parameters can be obtained from the construction BIM.

Metro construction risk is defined as the potential uncertainty causing economic loss, construction delay, human injury, and environment damage in the metro construction. The key to the risk identification process is to identify risk events and their risk factors, and their mutual relationships. Safety risks are related to many influential factors in metro construction projects, such as station/tunnel structural forms, construction techniques, geological and hydro-geological conditions and circumjacent environments. According to Ding et al. (2012), safety risks in metro construction can be divided into three categories: technical, geological and environmental risks. Accordingly, the information concerning (1) construction technology; (2) geological conditions; and (3) surrounding environment, is extracted from BIM where IFC plays a bridge role between the BIM data and metro construction safety risks.

SAFETY RELATED KNOWLEDGE MANAGEMENT IN METRO CONSTRUCTION

Historical safety-based knowledge resource provides massive prior knowledge for safety identification in metro construction. Unlike the traditional computer programming, the knowledge base is unique and plays a core role in an expert system. In this research, an integrated knowledge base, consisting of fact base, rule base and case base, is established to systematize the fragmented knowledge in metro construction.

Risk mechanism analysis and knowledge acquisition

During the knowledge base construction process, knowledge acquisition is the first step in an effort to identify relevant knowledge from the accumulated safety-based knowledge resources. This stage involves developing new knowledge content and updating old content through socialization, externalization, internalization, and combination (Alavi & Leidner, 2001). Anecdotal evidence suggests that the organizations could typically excel at this phase of the knowledge management, particularly in the construction industry where the knowledge storage and dissemination are inefficient and problematic (Hallowell, 2012). For hazard identification in metro construction, the risk factors of a specific risk can be acquired from the following two types of knowledge resources:

- Explicit knowledge. Explicit knowledge refers to the knowledge resource which can be easily codified and transmitted between individuals in documented and organized forms, such as standard specification, technical manuals and research reports. Evolution rules within potential risks and their risk factors can be clearly understood on a basis of this type of knowledge.
- Tacit knowledge. Tacit knowledge refers to the knowledge resource that is generally developed by an individual through experience. Dialogues and communications among individuals are the basic means of knowledge sharing. Therefore, questionnaire, depth interview and group decision making method can be adopted to reveal the potential risks and their risk factors. Also, numerous scholars built simulation models for the safety analysis, providing valid reference for the relation discovery within various risks (L. Y. Ding, Wu, Li, Luo, & Zhou, 2011; Ma, Luo, & Chen). Accordingly, the parameters of the simulation models can also be added as risk factors.

Fact base

Different values of a risk related parameter lead to the different credibility degree of the factor being considered as the evidence in accidence occurrence. The more difficult to become the evidence, the smaller its credibility factor (CF) is. Fact base is utilized to store the value of each risk factor, including the fact code, fact attribute and fact CF.

The range of risk factors can be divided into discrete and continuous values. For a risk factor with a discrete value, its fact CF is a discrete value. Taking the state of *"Retaining pile embedded into rocks* (e_1)" for an example, CF(e_1) is represented by "1" in the "*embedded into rocks*" state, otherwise as "0". While for a risk factor with a continuous value, its fact CF can be represented by a sectional function, and the sectional threshold value can be obtained from theoretical calculations or empirical formulas in the mechanism analysis. Taking the state of "*Water head difference between the inside and outside of a foundation pit* (e_2)" for an example, the water head difference x is a continuous value, and has a approximately linear relationship with the evidence credibility of e_2. Therefore, the sectional function expression for CF(e_2) is as follows:

$$CF(e_2) = \begin{cases} 0.2 & x < 2m \\ 0.8\dfrac{x-2}{4-2} + 0.2 & 2m \le x < 4m \\ 0.8 & x \ge 4m \end{cases} \quad (1)$$

Rule base

Existing knowledge representation methods consist of predicate logic, semantic network, production rule and frame method. Owing that the production rule "IF (premise) THEN (conclusion)" provides a powerful tool for knowledge representation and reasoning under uncertain environments, production rule could be employed to describe the empirical knowledge for safety risk identification. However, due to the lack of classification and relevance, this type of production rule is likely to cause combination explosion and low reasoning efficiency. Therefore, an extended representation of production rule as seen in Eq. (2) is adopted into the rule representation, with the hierarchy and uncertainty of rules being fully considered. The causal relationship between the premise (e) and the conclusion (h) is represented by Eq. (3).

$$If \quad e \quad Then \quad h \quad (CF(h,\ e),\ \lambda) \quad (2)$$

$$CF(h)=CF(h,\ e)\times CF(e) \qquad \forall\ CF(e) \ge \lambda \quad (3)$$

As seen in Eq. (3), λ refers to the rule threshold. The rule can be activated if and only if rule evidence CF (e) $\geqslant \lambda$. Generally, λ is defined to range from 0.5 to 1.0, depending on the importance of the project. The rule credibility CF (h, e) with a scope of [0, 1] , is related to the credibility degree of the rule (Cai & Xu, 2004).

Case base

A large amount of cases related to accident events and control response are accumulated, providing prior knowledge for risk identification in metro construction. By matching the characteristics of a specific project with cases in the case base, the potential accident events that are possible to occur can be detected ahead of time. Compared to rules, we do not need to construct explicit rule models as seen in Eq. (2) for case representation. Meanwhile, the case base is an open system, and easy to maintain. There is no need to perform dependency and consistency checking work while adding new cases into the case base.

To facilitate the efficiency during the case matching process, cases are required to be structured in accordance with the characteristic of domain cases. There are numerous methods for the case representation, including feature vectors, object, frame, and category representation method. Accident cases in metro construction generally display the characteristic of multi-level, multi-attribute and diversification. Therefore, a combination of frame and category representation method can satisfy the demand and be adopted for the case representation. A complete case record consists of attributes such as Construction Project Data (C_1), Accident Data (C_2), etc. Each attribute can then be further refined.

DEVELOPMENT OF B-RIES

In order to facilitate knowledge sharing and communication among dispersed clients and experts during the safety risk identification process, the integration of BIM and Expert System technique provides a full solution for the aforementioned deficiencies and shortages. A BIM-based Risk Identification Expert System (B-RIES) is developed to systematize the fragmented explicit and tacit knowledge in the metro construction. provides all the services for the system application, mainly consisting of three subsystems: BIM Extraction Subsystem (BES), Knowledge Base Management Subsystem (KBMS), and Risk Identification Subsystem (RIS). The user interface of the system is seen in Fig. 1. With the support of B-RIES, the safety risks can be identified automatically without abundant manual labors, together with the responding control measures. Generally, B-RIES would go through the following three steps during the safety risk identification process, as seen in Fig. 2.

Fig. 1--User interface of B-RIES

Engineering parameters extraction

BIM is considered as the information carrier of engineering parameters which are related to safety risks, and the IFC standard plays a bridge role between the BIM and metro construction safety risks. When BIM of a specific project, such as a metro station construction, is first input into the system, the IFC standard is employed to extract the information of model elements, including geometry, property and relation information for the engineering parameters. Then the parameter information is exported into the Extensible Markup Language (XML) format which is compatible with the system. In the meantime, the recognition results saved in XML format are in correspondence with the fact base. When the results are matched with the fact base, "element" in the XML files corresponds with Column "fact name" in the risk fact table. Consequently, the fact base is matched to calculate evidence credibility $CF(e)$ of the risk related engineering parameters. In this way, BES automatically extracts original and objective engineering parameters from BIM models without the involvement of abundant manual labors, greatly improving the low-efficiency in reading engineering drawings in traditional cases.

Knowledge inference mechanism

The knowledge inference mechanism endows the B-RIES with the artificial intelligence. Basically, the inference mechanism in expert systems consists of two approaches, namely rule-based reasoning (RBR) and case-based reasoning (CBR). RBR is known as a reasoning technique with powerful deductive inference capacity, and can be employed to deal with complicated realistic problems, such as goal programming, scheduling and budgeting (Kumar, Singh, & Sanyal, 2009). However, a RBR system is required to traverse the entire rule base during every reference process, leading to the problem of long retrieval time and low efficiency in rule retrieval, especially when the rule base is very large. In contrast, a CBR system attempts to seek the approximatively similar case using an analogous reasoning technique, and then make a corresponding adjustment for problem solving. The reasoning process is fast and efficient at the expense of in-depth analysis (Kumar et al., 2009). The CBR system has self-learning and self-improvement ability by adding new cases continually as the system operates. However, due to the lack of deductive inference capacity, the CBR system has deficiency in conformity with strict logical inference, leading to the problem of poor interpretability for the result.

In metro construction, complicated interaction among various risk factors contributes to the high level of safety violations. This produces a high demand for both rule-based and case-based knowledge during the risk identification process. Combining RBR and CBR techniques provide a solution for the above issue. It is also beneficial to improve the flexibility and comprehensiveness of system reasoning capacity simultaneously (Dzeng & Lee, 2004). Thus, a hybrid reasoning approach composed of four main sub-steps is adopted into B-RIES as follows:

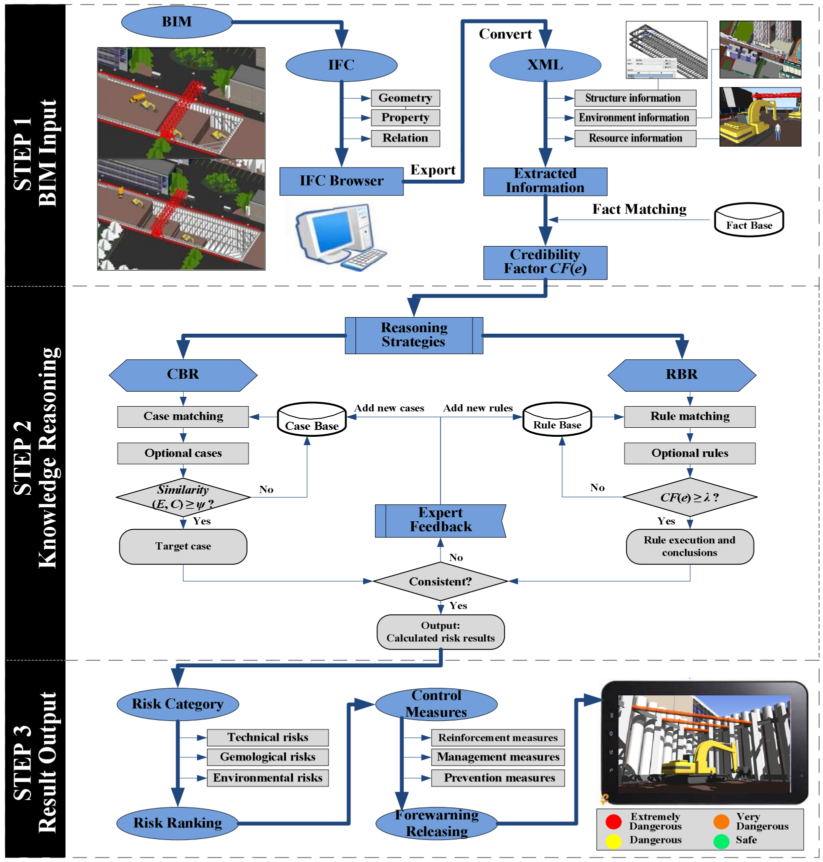

Fig. 2--Safety risk identification process in B-RIES

(1) CBR: Various historical safety related cases in metro construction fields are accumulated and then stored in the case base. The objective of CBR is to determine the most similar case as the target case. At first, the risk related engineering parameters information obtained from BIM is entered into B-RIES as evidence inputs. Then, the optional cases are selected after being matched with the case base. Finally, the target case is achieved if and only if the similarity is less than the given threshold ψ, as seen in Eq. (4).

Assuming each case has n attributes to describe the information of engineering parameters, the specific project is denoted by E=($CF(e_1)$, $CF(e_2)$, ... , $CF(e_n)$), and one optional case is denoted by C= ($CF(c_1)$, $CF(\mathrm{c}_2)$, ... , $CF(\mathrm{c}_n)$). Herein, $CF(e_i)$ (or $CF(\mathrm{c}_i)$) stands for the credibility factor of ith parameter for the specific project (or the optional case) while being matched with the fact base. The Euclidean distance, which is usually chosen as the similarity measure in the K-means clustering algorithm (Y. Ding, Krislock, Qian, & Wolkowicz, 2010), is adopted to calculate the similarity between E and S. As seen in Eq. (4), w_i stands for the weight of ith parameter based on the expert estimation and construction practice. The threshold ψ is usually has a value ranging from 0 to 0.5.

$$Similarity(E,C)=\sqrt{\sum_{i=1}^{n} w_i\left[CF(e_i)-CF(c_i)\right]^2}\le\psi, \qquad i = 1,2,...,\mathrm{n} \tag{4}$$

(2) RBR: RBR is also incorporated into the knowledge inference mechanism, aiming to figure out the valid rules which can then be executed in the following reasoning process. At first, the optional rules are selected from the rule base by means of rule matching. Next, the valid rule is reached if and only if $CF(e)$ is greater than the given threshold λ. In general, the premise evidence e is a combination of risk factors e_i (i=1,2,...,n), including disjunction, conjunction and weight combinations. Accordingly, $CF(e)$ is calculated by Eqs. (5)~(7), respectively. Finally, the valid rule is executed to calculate the credibility degree of the

conclusion of the safety related risk using former Eq. (3).

$$CF(e_1 \vee e_2 \vee \ldots \vee e_n) = max(CF(e_1), CF(e_2),..., CF(e_n)), \qquad i = 1,2,...,n \tag{5}$$

$$CF(e_1 \wedge e_2 \wedge \ldots \wedge e_n) = min(CF(e_1), CF(e_2),..., CF(e_n)), \qquad i = 1,2,...,n \tag{6}$$

$$CF(e_1(w_1) \wedge e_2(w_2) \ldots \wedge e_n(w_n)) = \sum_{i=1}^{n} w_i \times CF(e_i), \qquad i = 1,2,...,n \tag{7}$$

(3) Expert Feedback. As seen in Fig. 3, two approaches, CBR and RBR, are included in the knowledge inference mechanism. Then, the result calculated by one approach can be testified by the other. However, when the results are not consist between two, the domain experts should be involved to solve the problem by adding new rules or cases. In addition, the existing rules stored in the rule base might be modified according to the actual situation. The verified projects can also be added into the case base as new cases. With the continuous growth of the case base and rule base by means of this self-learning capacity in B-RIES, the accuracy and reliability of the system inference mechanism would be continuously improved with development of the system application.

(4) Reasoning Strategies. As aforementioned, the RBR approach would reduce the inference efficiency, especially when the scale of the rule base is very large. In order to keep a balance between the high efficiency and reliable accuracy, the reasoning strategies are carried out according to the phase of the system application. Specifically, in the initial stage of the system application, the number of rules (or cases) stored in the rule base (or case base) is relatively limited due to the lack of sufficient data. Also, the reliability of the initial rules need to be verified and improved by the real cases. Thus, RBR and CBR can work in a parallel way in this situation, contributing to expand the scale of the knowledge base by means of expert feedback. When the knowledge base grows large, these two approaches can work in a serial way for the consideration of space-saving in computation. Generally, CBR would be activated ahead of RBR as to avoid the low efficiency in rule retrieval. Once the target case is not reached in CBR, the RBR would then be activated.

Risk analysis and control

Based on the calculated results from the knowledge inference, the safety related risk analysis and control measures can be carried out. As seen in Fig. 2, the main identified safety risks/risk factors are first categorized into technical, geological and environmental risks. Combined with the risk ranking results, the corresponding safety control measures can then be achieved accordingly. Finally, the safety risk warnings are released in a visualization scenery. In the meantime, the identified safety risks, displayed by different colors in the visualization scene, can be divided into four levels, namely Red "Extremely dangerous", Orange "Very dangerous", Yellow "Dangerous" and Green "Safe".

CASE STUDY

Wuhan is the largest city in Central China with a population of 10.02 million (2011 data). In order to relieve the pressure of urban traffic jam across the Yangtze River, the construction of Wuhan Metro Line Two (WMLT) formally started on August 28, 2006. The 27.7km route, with 21 stations and a total investment of nearly US $3.2 billion, runs underground on a northwest-southeast alignment between the Hankou and Wuchang districts. B-RIES was applied to identifying safety risks at the pre-construction stage of metro construction, providing guidelines for safety assurance at the construction stage. A case concerning one metro station, Mingdu station, is presented in this paper for the system application.

Project profile

The Mingdu station, located in the Wuhan Metro Line Two, is an underground 2-story station. The station was started on November 26, 2008, with an outline length of 241.3 meters, an average width of 18.88 meters, and a total floor area of 11932.1 square meters. A foundation pit with a depth of around 15 meters was excavated using the cut and cover construction method. The retaining structure was composed of bored piles and jet grouting piles, which provided a waterproof curtain. Two adjacent high-rise buildings, Baoli Huadu Buildings, were located in the north of the foundation pit. The Tibetan Middle School was located in the south. The excavation space was limited due to the narrow working site.

Safety risk identification

With the support of the build-in subsystems of B-RIES, namely BES, KBMS and RIS, the results of safety risk identification in the Mingdu station were conducted, as seen in Fig. 3. Five main safety risks were identified, among which the risk of "flowing sand at the foundation pit bottom" was on the top of the list. In accordance with the safety risk identification process, the risk of "flowing sand at the foundation pit bottom" was taken as an example to present the detailed computation process.

Fig. 3--Results of safety risk identification in the Mingdu station

(1) Information extraction for engineering parameters. BIM (always in the format of Revit) related to the Mingdu station was first input into B-RIES. Next, the built-in recognition algorithms were aimed to extract the information for the risk related parameters where the IFC standard was acting as a bridge role between the BIM data and the risk related information. Then, the recognition results were stored in XML format files which could be read in B-RIES. The extracted information of risk related engineering parameters was seen in Fig. 4. Finally, the engineering parameters information saved in the XML files was matched with the fact base to calculate fact credibility $CF(e)$ of the risk related parameters. For instance, in XML files, an element was presented as "<state of bored pile embedded into rocks> not embedded into rocks", which means that "retaining pile embedded into rocks (e_1)" was in the state of " Not embedded". To be specific, the fact credibility of $CF(e_1)$ was recognized to be 1.0.

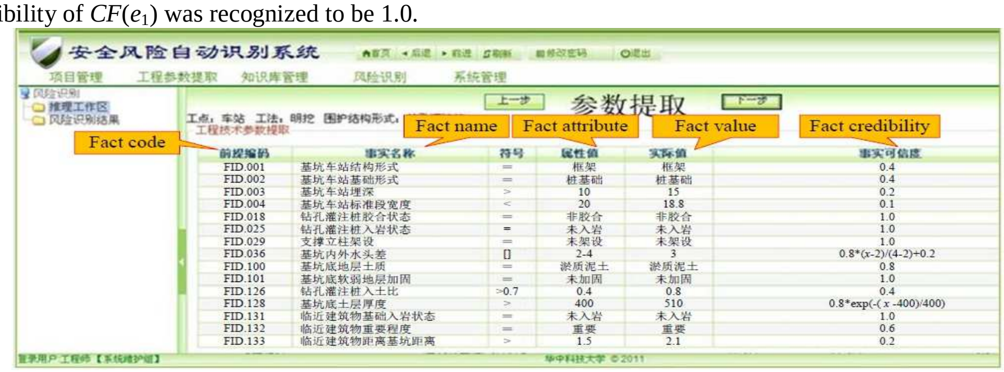

Fig. 4--Extracted information of risk related engineering parameters

(2) CBR approach. Based on the extracted risk related parameter information, Eq. (4) was used to find out the target case from the case base when CBR was activated. The target case was chosen to be the Guicheng station which is one station of the Guanzhou metro system in Guanzhou city, China, as shown in Fig. 5. The similarity between the specific project and the target was calculated to be 0.192 which was less than the given threshold ψ=0.3. In that accident, great quantities of sand swarmed into the Guicheng station under construction on July 31, 2008, resulting in serious ground subsidence and construction delay. According to the description of safety hazards in the target case, the project engineers came to have a deep understanding about the potential safety risks in the Mingdu station. Also, the risk level and relevant safety control measures were reached.

Fig. 5--Case matching results for the risk of flowing sand

(3) RBR approach. Based on the aforementioned procedure in the RBR approach, the rule base was

matched to select suitable rules. It is known that worksite type was "station" while the construction method was "cut and cover". Table 1 listed the optional rules for the risk of flowing sand. Using Eqs. (5)~(7), CF (*e*) of R1-11 and R1-14 is less than the threshold λ, therefore both were discarded. Next, CF (*e*) of R1-25 was calculated to be CF (*e*) = 1.0×0.2 + 0.6×0.2 + 0.8×0.25 + 01.0×0.3 + 0.4×0.1 + 0.6×0.1 = 0.76 > λ = 0.5. The rule R1-26 was therefore available, and Eq. (3) was used to calculate the conclusion credibility CF (*h*) = *CF*(*h* ，*e*)×*CF*(*e*)=0.76×0.8 =0.608.

Table 1-- Rule matching results for the risk of flowing sand

Rule code	Rule premise description	Worksite type	Construction method	Rule Credibility	Threshold λ
R1-11	¬FID.025∨ ¬FID.036∨ ¬FID.101	10	1110	0.5	0.9
R1-14	FID.025∧FID.036∧FID.100∧FID.101∧FID.126∧FID.128	10	1110	1	0.8
R1-26	FID.025(0.2)∧FID.036(0.2)∧FID.100(0.3)∧FID.101(0.1)∧FID.126(0.1)∧FID.128(0.1)	10	1110	0.8	0.5

(4) Risk identification and report. The results could be testified when RBR and CBR worked in a parallel way. In this case, the results were consistent between the two. The safety related risk analysis and control measures could then be obtained, such as risk type, description, location, possible consequences, risk level and control measures. The identification results of the risk of flowing sand in the Mingdu station was presented in Fig. 6.

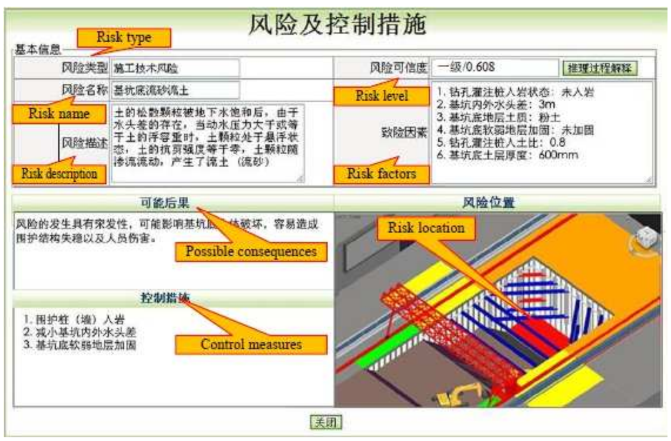

Fig. 6--Identification results for the risk of flowing sand

Implementing effects

According to the risk identification results from B-RIES in the Mingdu station, at the construction stage, the contractor strictly implemented the work of dewatering on working site, controlled the water head difference between the inside and outside of the foundation pit and reinforced the foundation pit bottom so as to reduce risk limit. In addition, the frequency of deformation monitoring was increased, ensuring the feedback analysis of measured data in the real time. Also, emergency supplies, equipment and personnel were prepared in advance to cope with the risk events which were very likely to occur. With effective safety control measures adopted, the construction of the Mingdu station in complex environments went smoothly and the main underground structural work was completed on August 9, 2010.

CONCLUSIONS

Numerous potential safety risks exist during the metro construction in complex project environments. Safety risk identification is becoming extremely important in the safety assurance in engineering practice. Large amounts of explicit and tacit risk-based knowledge provides sufficient prior knowledge for the risk inference process. B-RIES is developed to systematize the fragmented knowledge for knowledge sharing and communication among dispersed clients and domain experts. First, engineering parameter information related to risk factors are acquired from the BIM of a specific project where the IFC standard plays a bridge role between the BIM data and metro construction safety risks. A hybrid reasoning approach with CBR and RBR included is then proposed for knowledge inference. Finally, the results of safety related risks and their occurrence probability and control measures can be automatically achieved in real time. B-RIES can be used by practitioners in the industry as a decision support tool to provide guidelines on risk assessment and safety assurance in metro construction. Furthermore, B-RIES is worth popularizing in other similar projects where the risk management is closely related to the expert knowledge, such as coal mining, dam operation safety, nuclear power plants and others.

A large number of rules serving for safety risk identification were obtained from the domain experts on an empirical basis for this research. Numerous domain experts participated in the risk mechanism analysis work, making an essential contribution to securing a qualified rule base for the development of B-RIES. This process was laborious and relied greatly on the domain experts. Our subsequent research goal will focus on automatic knowledge acquisition regarding different knowledge resources, as well as adopting the Rough Set (RS) to develop a real-time intelligent rule-based system.

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