INTEGRATION OF INTELLIGENT MODELS AND SENSING TO PREVENT HARDLY PREDICTABLE HAZARDS IN CONSTRUCTION SITES

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ABSTRACT

This article reports on the current state of an ongoing research project which is aimed at implementing intelligent models for hardly predictable hazard scenarios identification in construction sites.

As past evidences showed that no programmatic action can deal with the unpredictable nature of many risk dynamics, we tried to survey on how the current approach for safety management in the construction industry could be improved. In our previous research the use of Bayesian networks elicited from subjective knowledge were preliminarily tested. Those networks might be meant as a reliable knowledge map about accident dynamics and they showed that a relevant ratio of occurrences fall in "hardly predictable hazards" class, which cannot be warded off by programmatic safety measures.

This paper reports the second outcome of our research project, which focused on the development of first elementary fragments, regarding the occurrence of a possible "hardly predictable scenario". Instead of experts' contributions (who, over their carrier, seldom incurred in accidents), we used "legal cases" as an accurate source of information. They suggested which categories of "hidden hazard scenarios" are more likely to happen. We found that the most frequent hidden hazard scenarios are linked to operator's negligence and abnormal behavior, e.g. irregular removal of scaffolding's components, unprotected openings, improper use of PPE, etc. Every pattern determined by legal cases has been formalized by a fragment (i.e. elementary network) of the overall Bayesian network.

Finally, all the elementary networks were integrated into a comprehensive intelligent tool for real-time hardly predictable hazards prevention. The final setup, asked for interfacing these intelligent models to a low-level sensor network and used to feed them with inputs about the current state of the context, is discussed too.

KEYWORDS

Intelligent models, pervasive sensors, health and safety, Bayesian networks, construction sites.

INTRODUCTION

This article reports the current progress of an ongoing research project, supported by Cagliari University and Polytechnic University of Marche – Ancona, both being Italian institutes. The project is aimed at implementing intelligent models for "hardly predictable hazard scenario" identification in construction sites.

Nowadays, the standard approach to health and safety management in the construction industry usually starts off with the identification of task sequences at the design phase. Then, preventive or protective actions are defined and H&S Coordinator is appointed to supervise during the execution phase (Aulin & Capone, 2010). So far, great attention has been paid to prevention. In the USA the National Institute for Occupational Safety and Health (NIOSH) promoted the PtD strategy (Behm, 2010; Gambatese & Hinze, 1999), meaning that prescriptions shall be incorporated into the process of design and redesign of work premises, resources and processes. Every approach is generally based on the analysis of risk scenarios for each task and interfering activities (Gangolells et al., 2010). Indeed, they follow the Plan Check Do Act (PCDA) cycle (BS OHSAS 18001). The weakest aspect of this traditional approach lays in the high costs tied to monitoring and control, due to the required enduring presence on site of the H&S Coordinator. In addition, statistics clearly show that the present programmatic approach has determined no breakthrough. Construction sites are still among the most dangerous workplaces and the number of accidents reaches up to 10-11% of the overall manufacturing sectors. Although fatal accidents in EU is decreasing (less than 3 fatalities per 100,000 employees), the construction industry's exceeds 10 fatal accidents per 100,000 employees, the most frequent cause being fall from height (Eurostat, 2011). Similarly was noted by US and Israeli surveys: on-site accidents represent one third out of the total and 60%, respectively (Navon & Kolton, 2006).

For that reason, a continuous control of work phases is needed, which would be not feasible by means of mere physical supervision. Hence the development of new methods allowing a cut-down in control costs through automatic monitoring systems is wished. The new systems must be able to warn in case of hazard occurrence, allowing for the adoption of corrective counteractions in real time. To this purpose, tests on instruments to track in real time workers present on the site have been carried out. This was meant to reduce interferences between different teams (Swedberg, 2006). Other systems for reducing risks regarding workers being run over by site equipment have been experimented like, for example, UWB radar systems installed on dumpers used in caves (Zetik et al., 2007). Following another approach (Caldas et al., 2006), a 3D model was built from the data acquired by a LADAR (Laser Detection and Ranging) scanner so as to recreate the bulk of heavy objects present on the site and run collision avoidance procedures. A safety helmet for workers in construction sites was enhanced to accommodate miniature positioning and communication instruments (Abderrahim et al., 2005). A mobile sensing device for detecting the worker's approach towards floor openings was proposed (Kim et al., 2009). Here the contribution given by ICT devices is critical to data gathering and their immediate elaboration, provided that tracking systems are low-intrusive and are able to gather information in real-time. An ultra-wideband (UWB) wireless and untethered network system for mobile asset tracking at a dynamic construction site was tested (Cho et al., 2010). Its performances were good, at the expense of a bit loss of accuracy, with respect to the basic tethered UWB system (Saidi et al., 2011). Combining non-invasive tracking systems with dedicated intelligent control logics, would make the automation of many important tasks for construction sites feasible (Lu et al., 2011).

Another approach to safety is represented by the substitution of human labor with machines to perform dangerous tasks. One example is given by the specially designed light-weight robotic tool, for the application of advanced composite materials and epoxy resins during tunnel excavation (Victores et al., 2011). Another one was proposed to prevent man-hook crane collisions (Tantisevi & Akinci, 2007).

In this paper we present an intelligent probabilistic model, which is expected to be able to filter and translate sensor data into probabilistic inferences, in order to assess the likelihood of accident occurrence in real time. The model was developed in the form of Bayesian networks (Pearl, 1988). It follows some past research, which already led to a first relevant result: a Bayesian network for safety management in the "fall from height" hazard was worked out through an elicitation process from subjective knowledge (Argiolas et al., 2012). As a first outcome, it allowed the combination of several sources of knowledge into a comprehensive knowledge map. Moreover the several dynamics leading to the falls from height occurrence were homogeneously represented. As a second outcome, that network suggested that two main different types of hazardous events might reasonably occur in the case under analysis: on the one hand the predictable ones (i.e. "detectable hazard"), which can be assessed and mitigated at the planning phase; on the other hand, the "hidden" (i.e. "hardly predictable") ones, which are so called because they can be identified through the models but whose accurate assessment is hampered by their variability with the context's evolution and the degree of occurrence of several external factors or of weird interferences among different teams.

Hence, further efforts turned out to be needed in order to manage those hidden and/or hardly predictable hazardous scenarios. In order to find out how those dynamics take place, we decided to analyze "legal cases" as our source of information: each pattern determined by legal cases was expected to suggest a class of "hidden hazard scenario", then to be translated into a network fragment.

In the rest of this paper, we will deeply analyze many legal cases, in order to work out new network fragments, one for each possible hidden scenario, then to be integrated into the overall network. Among the many hazards, we focused the fall from height scenario caused by unprotected openings. Our legal cases clearly show that these occurrences often lead to permanent disability or death. Then the way automatic supervision or compliance to the safety rules and regulations can be implemented in the execution phase was analyzed. Such scenarios were formalized as a set of Bayesian networks, in order to form the basis for the development of real time instruments for health and safety management.

METHODS

Data and information gathering

Legal cases have been considered as the most reliable, complete, objective and accurate source of data and information. We have examined, in particular, legal cases of the Italian Court of Cassation (the Supreme Court in other countries). Basically, two reasons have led to the use of this source over other alternative ones. First, the experience of the domain experts modeled in our previous work (Argiolas et al.,

2012) was limited to a subjective estimation of frequencies of occurrence and detectability level of “falling from heights” hazard. But, in order to be applied to real cases, intelligent models must manage every specific occurrence of “falling from height” hazard (e.g. falling from unprotected openings); in this field, experts in their carrier have hardly incurred in a significant number of one specific kind of accident. Secondly, data and information from INAIL databases (i.e. the Italian National Institute for Insuring Hazards at Work) are not detailed enough to support analyses of accident dynamics.

For both reasons, we tried to survey on legal cases, because they include a significant of the way such accidents take place. We have analyzed about 100 legal cases of the Italian Court of Cassation. In particular, we have gathered legal cases which, belonging to the field of safety in construction sites, focus on falling from height scenario. To the purpose of the research reported in this paper, we have identified accident dynamics relative to falling from “floor unprotected openings” category, which shows high frequency of occurrence. After their identification, we developed a standard form (Figure 1), which was aimed at highlighting relevant data and information about each picked legal case.

REFERENCES	TITLE		
	NUMBER		
	YEAR		
TYPE OF VENUE		PRIVATE BUILDING SITE	
		PUBLIC BUILDING SITE	
TYPE OF BUILDING INTERVENTION		CONSTRUCTION	
		RESTRUCTURING	
		MAINTENANCE	
ACTIVITY CARRIED OUT BY INJURED WORKER			
INJURED WORKER		CONSTRUCTION WORKER (CONTRACTOR)	
		CONSTRUCTION WORKER (SUBCONTRACT)	
		EMPLOYER	
		CONSTRUCTION FOREMAN	
		OTHER	
EVENT CLASSIFICATION		INJURY	PERMANENT DISABILITY
			DEATH
		NO PROTECTION	
SUMMARY OF DYNAMIC			
TRIGGERS		OPENINGS (Ø>40CM)	
		LOW DISTANCE (WORKER-OPENING)	
		NO RAILING	
		WEAK RAILING	
		NO FILLING	
		WEAK FILLING	
		NO SAFETY NET	
		INCOMPLETE SAFETY BELTS	
		NO SAFETY BELTS	
		FLOOR TILT	

Figure - 1 Data and information gathered for each legal case

Development of the qualitative Bayesian network

By means of the above form (Figure 1), legal cases relative to falling from floor unprotected openings have been collected and their triggers and dynamics noted down. Information gathered in this phase allowed us to state that as for 53% of the selected legal cases, accidents were due either to an irregular use of collective protective equipment (i.e. railing along the opening perimeter and sheets of timber to prevent falling inside) or to lack of personal protective equipment (sometimes because of the negligence of employers and some other times due to the abnormal behavior of operators who do not use PPE at all). In 43% of the analyzed legal cases, falling from floor unprotected openings were caused by lack of protective measures to mitigate and reduce risks (i.e. safety equipment). Finally, 4% of the accidents were caused by concurrent absence of collective safety measures and equipment and, at the same time, by wrong use of personal protective equipment (e.g. wearing safety belts not secured to anchors).

Through the information gathered in this phase, the qualitative structure of the Bayesian Network shown in figure 2, was worked out. We have chosen the Bayesian causal models because of their potentials to integrate several sources of information and to perform estimations in real-time (Argiolas, 2012). This first structure of the network was intended as the kernel of any more advanced models, where new nodes shall be added, when further evidences will be collected.

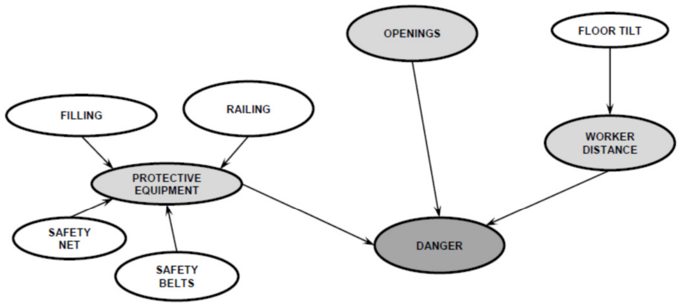

Figure - 2 Falling from floor unprotected openings: the qualitative BN structure

Finalization of the Bayesian Network

All the forms deriving from the analysis of legal cases, like in Figure 1, were rearranged into a new database, where each record referred to - at least - one occurrence of accident and contained the state of every variable (or node) of the Bayesian Network in Figure 2. Some accidents were suggested by more than just one legal case, which happened for those dynamics which are very likely. Figure 3 shows a database's excerpt: the column headers represent all the BN's variables. Each row defines the states of all the variables involved in each of the legal case analyzed.

In order to perform the learning phase of the network, the database's structure has been extended with all the other combinations of variables, which are complementary to the legal cases analyzed and which describe the situations which did not lead to accidents, thus the database also expressed those combinations where safety was regularly managed. The final database contained 44 records. The learning process was based on the EM (Expectation Maximization) algorithm, which estimates the hyper-parameters of Dirichlet distributions among the connected nodes (Heckerman, 1996).

Danger	Openings	Distance	Railing	Filling	Net	Belts	Floor
True	Vane	Near	None	None	False	None	Plane
True	Vane	Near	None	None	False	None	Sloped
True	Vane	Near	Weak	None	False	None	Plane
True	Vane	Near	None	Weak	False	None	Plane
True	Vane	Near	None	Weak	False	Incomplete	Sloped
True	Vane	Near	Weak	Weak	False	None	Plane
True	Vane	Near	None	None	False	Incomplete	Sloped
True	Vane	Near	None	Weak	False	None	Sloped
False	Vane	Near	Bearing	None	False	None	Plane
False	Vane	Near	Bearing	None	True	None	Plane
False	Vane	Near	Bearing	None	False	None	Sloped
False	Vane	Near	None	Bearing	False	None	Sloped
False	Vane	Near	None	None	True	None	Sloped
False	Vane	Near	None	None	False	Regular	Sloped
False	Vane	Near	Bearing	Bearing	False	None	Sloped
False	Vane	Near	Bearing	None	True	None	Sloped

Figure 3 – An excerpt from the database

RESULTS

The network was implemented in the Hugin Expert^{TM} software program and preliminary tests were performed to assess its sensitivity to the relevant inputs for risk estimation. The first scenario in Figure 4 shows a safe condition, relative to a worker who is working near a large opening (diameter > 40 cm) which is protected by a regular railing. The scenario in Figure 5-a shows a safe operational condition for a worker who is far from a large unprotected opening (diameter > 40 cm). The last scenario (Figure 5-b) simulates the case of a highly unsafe working condition for a worker who is working near a large and unprotected opening (diameter > 40 cm), given that the worker does not regularly wear personal protective equipment (e.g. safety belts are not properly anchored). Hence the network was shown to be able to automatically discern those cases which could easily lead to accidents.

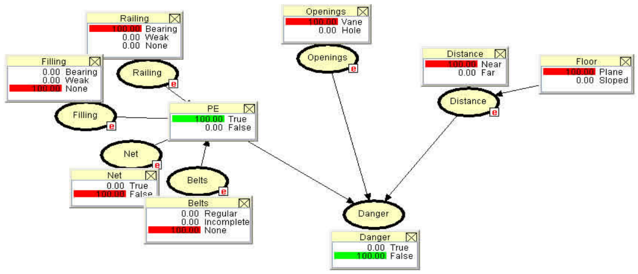

Figure - 4. Safe scenario in case of large opening protected by regular railing.

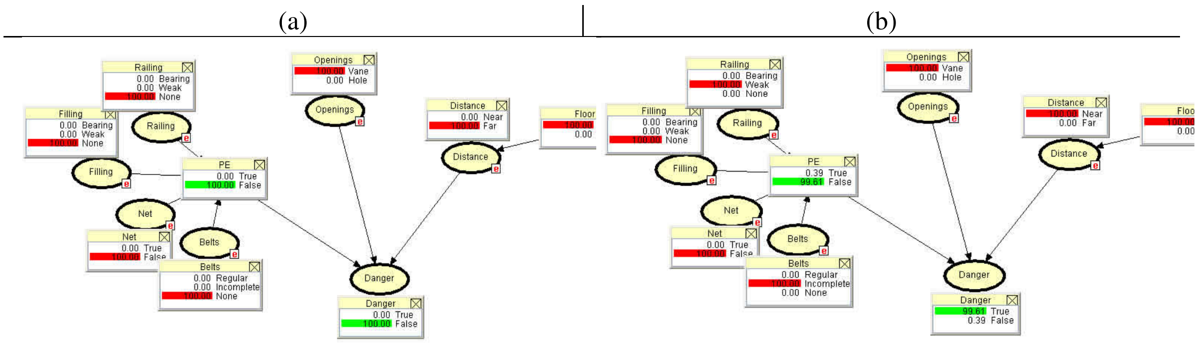

Figure - 5. Another safe scenario (a) and one unsafe scenario due to irregular use of PPE (b).

DISCUSSION

Thanks to this network, the possible chain of events which might potentially lead to falling from floor openings have been formalized. The model was developed in the form of a Bayesian Network and, provided it is inputted with real time data on the state of the context (i.e. distance between workers and openings, opening size, floor slope, protective equipment etc…), it can estimate the potential for hazards. In fact, it was meant as a substitute/support to on-site human control of compliance to safety regulations.

In order to be intelligent and react in real-time, such model needs a sensor setup to monitor the state of context's variables and gives them as input to the network. Sensors will update nodes' beliefs in real-time; then the network will propagate that belief and estimate the probability of occurrence of falling from floor openings. So this is our first brick to produce a real-time monitoring system to identify unpredictable triggers which could determine risk of falling from heights.

As the last step, those sensors needed to collect in real-time context's information were assessed. According to the qualitative structure of the network, the first variable to be monitored is the presence of floor openings. Hence, during a site's progress, dedicated sensors will be installed in the internal perimeter of each floor opening. The sensor is supposed to be able to measure the opening's size, and determine whether it has a diameter higher than 0.40 m, that is the minimum through which a person can fall through.

Other sensors to be located on-site will be meant to:

- estimate the distance between workers and floor openings (e.g. by means of tracking systems);
- assess the proper use of collective protective equipment - CPE (such as railing and safety nets);
- assess the correct use of personal protective equipment - PPE (e.g. safety belts).

These inputs are needed by the Bayesian Network to make inferences and estimate the actual risk level in real-time. Of course some estimations are not so straightforward and must be adapted to specific situations: e.g. workers walking on sloped roofs must be kept farer from unprotected floor openings than those working on flat floors, due to risk increases by the possibility of sliding and rolling towards openings.

Another set of sensors was meant to continuously check the compliance of CPE to safety measures. That's needed because a wrong CPE installation (e.g. missing railings and under-sized timber sheets) may cause a risk. Also, to be identified those cases when an operator in charge of manually checking CPE compliance must be appointed: it is necessary every time some irregularities cannot be automatically discerned, e.g. weak railing and timber sheets not firmly installed.

Finally, a third set of sensors should be installed in order to control the correct use of PPE. As falling from floor unprotected openings scenario is often linked to an irregular use of PPE (e.g. worn safety belts but not firmly secured), they are expected to check whether:

- safety belts are correctly worn;
- safety belts are correctly secured to their anchor points;
- anchor points and/or anchor lines are regular.

The availability of the sensor setup described above will allow to monitor in real-time operational conditions which could determine the occurrence of hazards. Those data would transfer such raw information to the yellow "root nodes" pictured in Figure 6. So the overall Bayesian Network was worked out, which not only includes inference models to estimate how likely hazard occurrence is, but also can accept data from sensors to perform such inference in real-time.

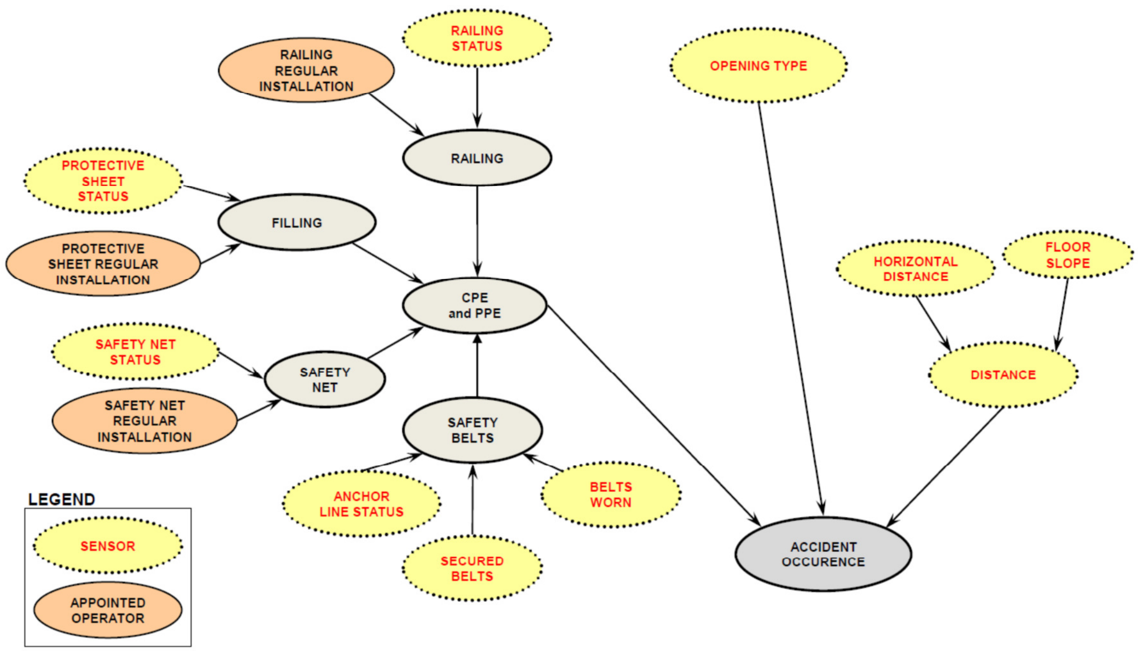

Figure 6 – Input nodes of the net

CONCLUSIONS

Our approach rises from the need to develop intelligent models based on Bayesian Networks and capable of checking the occurrence of hardly predictable risks in real-time. The models we propose to identify those risks own two features:

- firstly, they must be able to warn whether any hazard situations occurs in real-time;
- secondly, they must make inferences automatically, hence they must run given inputs periodically sent by sensors.

In particular, in this paper a first intelligent model, in the form of Bayesian network, estimating the "fall from unprotected openings" risk scenario, was developed. It was also successfully validated through preliminary tests. Data were retrieved from the analysis of legal cases, which helped identify those dangerous scenarios which could reasonably lead towards the occurrence of accidents. Those data were translated into a list of records, which were used to perform the network's learning. All the root nodes were set as inputs provided by a set of sensors, which will make the network autonomous in the task of supervision of the context evolution, potentially leading to accidents. Hence, the intelligent model is ready for further integration with the suggested sensor network, capable of tracking abnormal behavior and operator's negligence (i.e. "near miss accident" – according to OHSAS 18000).

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