



Knowledge Based System for the Evaluation of Safety and the Prevention of Railway Accidents

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ABSTRACT

This paper describes a contribution to improving the usual safety analysis methods used in the certification of railway transport systems. The methodology is based on the complementary and simultaneous use of knowledge acquisition and machine learning. The purpose is contributed to the generation of new accident scenarios that could help experts to conclude on the safe character of a new rail transport system. The method of analysis and evaluation is centered on the summarized failures (SFs) which are involved in accident scenarios capitalized. A summarized failure (SF) is a generic failure produced by the combination of a set of basic failures which has the same effect on the performance of the system. Each scenario brings into play one or more SFs.

The purpose is to automatically generate a recognition function for each SF associated with a scenario class. The SF recognition function is a production rule which establishes a link between a set of facts (parameters which describe a scenario or descriptors) and the SF fact. A base of evaluation rules can be generated for each class of scenarios. The SF deduction stage requires a preliminary phase during which the rules which have been generated are transferred to an expert system in order to construct a scenario evaluation knowledge base. The evaluation knowledge base is exploited by forward chaining by an inference engine and generates the summarized failures (SFs) which must enter into the description of the scenario which is to be evaluated.

1. Introduction

The Three main players, each with distinct roles, are involved in developing and operating an automated guide way transit system. The manufacturer validates the system, the chief contractor (or the customer) approves the system and the State or the local authority supervises that all those who are involved meet technical safety requirements. It issues commissioning authorizations which may be withdrawn if there is a failure to comply with safety requirements which apply to design, manufacture or operation. State departments generally make use of external audits or expert bodies such as IFSTTAR in order to draw up certification notices. The modes of reasoning which

are used in the context of certification (inductive, deductive, analogical, etc.) and the very nature of knowledge about safety (incomplete, evolving, empirical, qualitative, etc.) mean that a conventional computing solution is unsuitable and the utilization of artificial intelligence techniques would seem to be more appropriate. This research has involved three specific aspects of artificial intelligence: knowledge acquisition, machine learning and knowledge based systems (KBS). Development of the knowledge base in a KBS requires the use of knowledge acquisition techniques in order to collect, structure and formalizes knowledge. It has not been possible with knowledge acquisition to extract effectively some types of expert knowledge. Therefore, the use of

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knowledge acquisition in combination with machine

The approach which was adopted in order to design and implement an assistance tool for experience feedback involved the following two main activities [1]:

– Extracting, formalizing and storing hazardous situations to produce a library of standard cases which covers the entire problem. This is called a historical scenario knowledge base (HSKB). This process entailed the use of knowledge acquisition techniques,

– Exploiting the stored historical knowledge (experience feedback) in order to develop safety analysis know-how which can assist experts to judge the thoroughness of safety analysis. This second activity involves the use of machine learning techniques and expert system.

This paper presents the result of these two research activities which are involved in the methodology of safety analysis of guided rail transport systems.

2. Knowledge Acquisition and Machine Learning

Knowledge acquisition was recognized as a bottleneck from the first appearance of expert systems, or more generally knowledge based systems (KBS) [2]. It is still considered to be a crucial task in their creation. Extraction or elicitation refers to the collection of knowledge from experts in the field whereas the concepts of transfer or transmission of expertise refer to the collection and subsequent formalization of the knowledge of a human expert. The term knowledge acquisition refers to all the activities which are required in order to create the knowledge base in an expert system. Knowledge acquisition (KA) is one of the central concerns of research into KBSs and one of the keys not only to the successful development of a system of this type but also to its integration and utilization within an operational environment. Two main participants are involved in KA [2], [3]: the expert, who possesses know-how of a type which is difficult to express, and the cognitive scientist who has to extract and formalize the knowledge which is related to this know-how, which as far as the expert is concerned is usually implicit rather than explicit.

learning appears to be a very promising solution.

Currently available KA techniques mainly originate in cognitive psychology (human reasoning models, knowledge collection techniques), ergonomics (analysis of the activities of experts and the future user), linguistics (to exploit documents more effectively or to guide the interpretation of verbal data) and software engineering (description of the life cycle of a KBS) [2], [3] and [4].

Although cognitive psychology and software engineering have produced knowledge acquisition methods and tools, their utilization is still very restricted in a complex industrial context. Transcribing verbal (natural) language into a formal language which can be interpreted by a machine often distorts the knowledge of the expert [2], [4].

This introduces a bias in passing from the cognitive model of the expert to the implemented model. This disparity is in part due to the fact that the representational languages which are used in AI are not sufficiently rich to explain the cognitive function of experts and in part to the subjective interpretation of the cognitive scientist. These constraints act together to limit progress in the area of knowledge acquisition. One possible way of reducing these constraints is combined utilization of knowledge acquisition and machine learning techniques. Experts generally consider that it is simpler to describe examples or experimental situations than it is to explain decision making processes. Introducing machine learning systems which operate on the basis of examples can generate new knowledge which can assist experts in solving a specific problem. The know-how of experts depends on subjective, empirical, and occasionally implicit knowledge which may give rise to several interpretations. There is generally speaking no scientific explanation which justifies this compiled expertise. This difficulty emanates from the complexity of expertise which naturally encourages experts to give an account of their know-how which involves significant examples or scenarios which they have experienced on automated transport systems which have already been certified or approved [5].

Consequently, expertise should be updated by means of examples. Machine learning can facilitate the transfer of knowledge, particularly when its basis consists of experimental examples [6], [7] and

[8]. It contributes to the development of the knowledge bases while at the same time reducing the involvement of cognitive scientists. In our approach, learning made use of the HSKB to

Machine learning is defined by a dual objective [9]: a scientific objective (understanding and mechanically producing phenomena of temporal change and the adaptation of reasoning) and a practical objective (the automatic acquisition of knowledge bases from examples). Learning may be defined as the improvement of performance through experience. Learning is intimately connected to generalization: learning consists of making the transition from a succession of experienced situations to knowledge which can be re-utilized in similar situations. Expertise in a domain is not only possessed by experts but is also implicitly contained in a mass of historical data which it is very difficult for the human mind to summarize. One of the objectives of machine learning is to extract relevant knowledge from this mass of information for explanatory or decision making purposes. However, learning from examples is insufficient as a means of acquiring the totality of expert knowledge and knowledge acquisition is necessary in order to identify the problem which is to be solved and to extract and formalize the knowledge which is accessible by customary means of acquisition. In this way each of the two approaches is able to make up for the shortcomings of the other. In order to improve the process of expertise transfer, it is therefore beneficial to combine both processes in an iterative knowledge acquisition process (Figure 1).

Our approach has been to exploit the historical scenario knowledge base by means of learning with a view to producing knowledge which could provide assistance to experts in their task of evaluating the level of safety of a new system of transport.

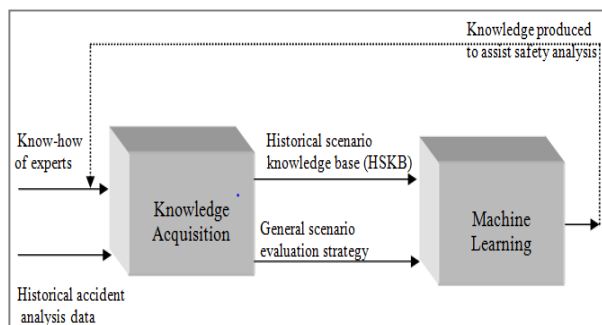


Figure 1: The general processes of safety knowledge acquisition

generate new knowledge likely to assist experts evaluates the degree of safety of a new transport system.

3. Methodology for the Analysis and Assessment of the Safety of Railway Transport

The method of analysis and evaluation of experience feedback is centered on the summarized failures (SFs) which are involved in accident scenarios capitalized. A summarized failure (SF) is a generic failure produced by the combination of a set of basic failures which has the same effect on the performance of the system. Each scenario brings into play one or more SFs. A list has been compiled of the SFs involved in all the scenarios which have been collected so far. The following list is a sample of a few SFs:

SF1: train reversing into an occupied block

SF2: collision avoidance transmitter failure in a train

SF3: masking of an alarm by initialization

The methodology proposed analysis involves six phases [10] (Figure 2):

- Acquisition and modeling of safety knowledge,
- Learning descriptions of the classes of accident scenarios,
- Classification (deduction) of a new example of a scenario,
- Elaboration of the base of learning centered on the SFs which are involved in Ck,
- Learning the SF recognition functions,
- Deduction of SFs that are to be considered in the new scenario.

4. Acquisition and Modeling of Safety Knowledge

This first stage involves the collection of safety analysis knowledge with respect to automated transport systems. This knowledge is as follows [1], [5] and [10]:

- The HSKB which consists at present of about sixty historical scenarios which relate to a

collision hazard. These scenarios have been formalized on the basis of a static description then placed in classes by the expert,

- An accident scenario description language, which consists of a set of descriptors (or parameters which describe a scenario),
- Accident scenarios which are described using this language. These may be historical and pre-classified by the expert in order to add to the HSKB, or new and suggested by the manufacturer. In the second case the experts will attempt to evaluate the consistency of the scenarios,
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- Learning parameters (induction, classification and convergence parameters).

The scenarios which have been collected together so far in the historical knowledge base relate to the collision problem and have been constructed on the basis of the safety dossiers of rail transport systems

French: VAL, POMA 2000, MAGGALY and TVM430 (Nord TGV) systems and the know-how of experts. More precisely, the level of detail which is required in system description in order to formalize the scenarios relates essentially to the general specifications of the system, the functional specifications and functional safety analysis (FSA).

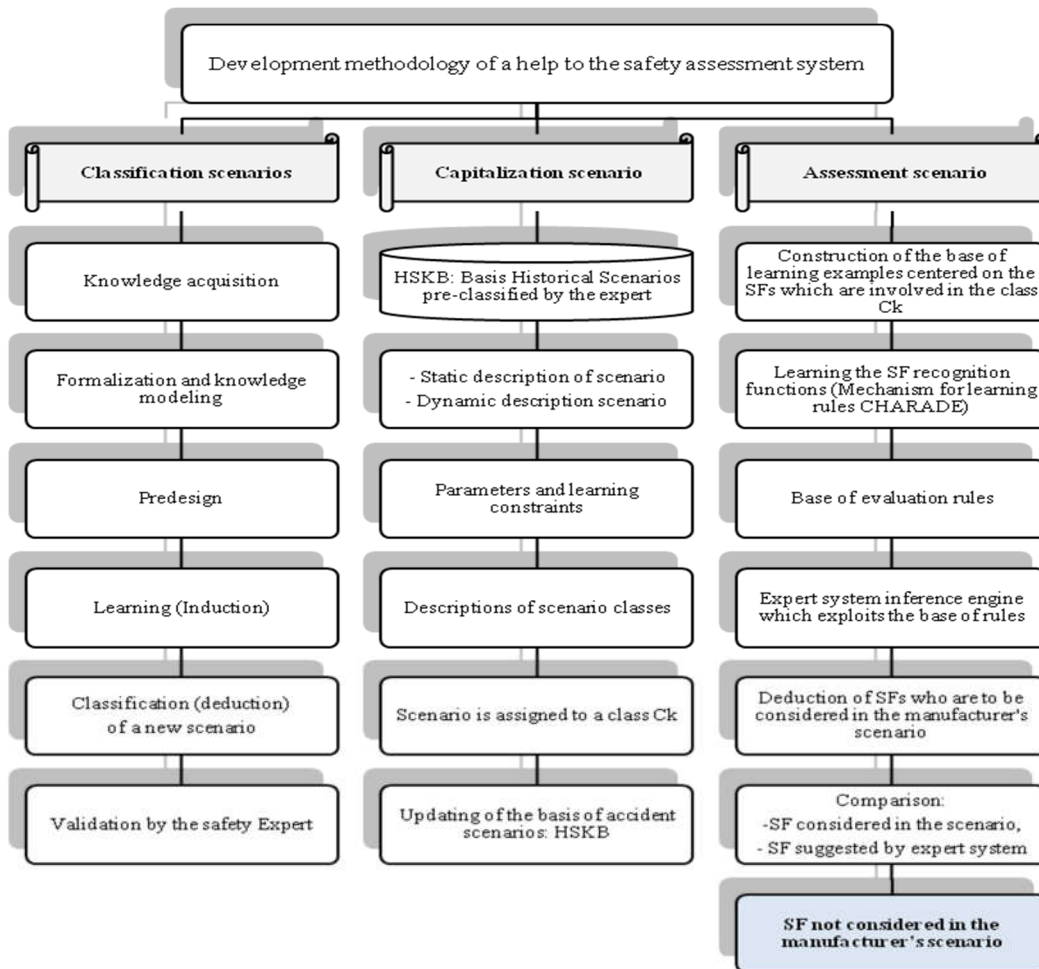


Figure 2: Functional description of the methodology of analysis and safety assessment

An accident scenario describes a combination of circumstances which can lead to an undesirable, perhaps even hazardous, situation. It is characterized by a context and a set of events and parameters. Knowledge acquisition led to the development of a model which is essentially based on the identification of the eight parameters which describe an accident scenario [1] (Figure 3). Examination of the concept of scenario revealed two fundamental aspects. The first is static and characterizes the context. The second is dynamic and shows the possibilities of change within this context, while stressing the process which leads to an unsafe situation. In the case of dynamic description the formalism of Petri Nets is adopted

The form adopted for the static description is that of a list [1] (Figure 3) in which several essential descriptive parameters are described in attribute/value terms. Very schematically, guide way transit systems are considered as being an assembly of basic bricks and a new system possesses certain bricks which are shared by systems which are already known. In the context of this study the basic bricks which have currently been identified have been grouped together in the descriptive sheet, and the tool finds and then exploits shared bricks in order to deduce the class to which a new scenario belongs or evaluate its completeness.

5. Induction of Description of Classes of Scenarios

This stage involves generalizing the classes which have been pre-defined by the experts in order to generate a comprehension description for each class which both characterizes the division which has been conducted by the expert and makes it possible to identify to which class the new example belongs. Each description which is learnt is characterized by a combination of three elements: (<Attribute><Value><Frequency>). The frequency of appearance is computed for each descriptor (attribute/value) in order to limit the loss of information [11]. The description of a class is further enriched by taking into account the associated summarized failures (SF) which are involved. These SFs will subsequently be exploited in order to develop the base of learning examples.

6. Classification of a New Example of a Scenario

In this stage a new example of a scenario is assigned to an existing class C_k . For this it is necessary to define a classification criterion which measures the degree of resemblance between the new example and each of the pre-existing classes. This similarity criterion is based on statistical calculations and takes account of the semantics of the domain of application. In the situation where tool has assigned the new example of a scenario to a class, this class needs to be updated. The updating process generates four situations as below [11]:

- The phenomenon of particularization of descriptors: descriptors which are considered characteristic at the instant t may lose their significance at the instant $(t+1)$,
- The phenomenon of generalization of descriptors: descriptors which are considered not to be meaningful may become characteristic,
- Phenomena of simultaneous particularization and generalization, – The learning of new descriptors which enrich the description of the class.

This phenomenon demonstrates the no monotonic character of learning.

7. Construction of the Base of Learning Examples Centered on the SFs

The base of learning examples for a class is obtained by grouping together scenarios from the HSKB whose description involves SFs from this class. This base is created from classification results and exploited by a rule learning system which constructs a knowledge base for evaluating accident scenarios. The format of this base is compatible with that required by the CHARADE [9] learning mechanism. The base is refreshed each time the classes suggested by tool are updated. CHARADE [9] is a learning system whose purpose is to construct knowledge based systems on the basis of examples. It makes it possible to generate a system of rules with specific properties. Rule generation within charade is based on looking for and discovering empirical regularities which are present in the entire learning sample. Regularity is a correlation which is observed between descriptors in

the base of learning examples. If all the examples in the learning base which possess the descriptor d1 also possess the descriptor d2 it can be inferred that $d1 \rightarrow d2$ in the entire learning set. In order to illustrate this rule generation principle let us assume that there is a learning set which consists of three examples E1, E2, and E3.

$$E1 = d1 \ \& \ d2 \ \& \ d3 \ \& \ d4$$

$$E2 = d1 \ \& \ d2 \ \& \ d4 \ \& \ d5$$

$$E3 = d1 \ \& \ d2 \ \& \ d3 \ \& \ d4 \ \& \ d6$$

CHARADE [9] can in this case detect an empirical regularity between the combination of descriptors (d1 & d2) and the descriptor d4. All those examples which are described by d1 & d2 are also described by d4. The rule $d1 \ \& \ d2 \rightarrow d4$ is obtained.

8. Learning the SF recognition functions

This phase of learning attempts, using the base of sixty examples which was formed previously, to generate a system of rules. The purpose of this stage is to generate a recognition function for each SF associated with a given class. The SF recognition function is a production rule which establishes a link between a set of facts (parameters which describe a scenario or descriptors) and the SF fact. A base of evaluation rules can be generated for each class of scenarios. The conclusion of each rule which is generated should contain the SF descriptor or fact. It has proved to be inevitable to use a learning method which allows production rules to be generated

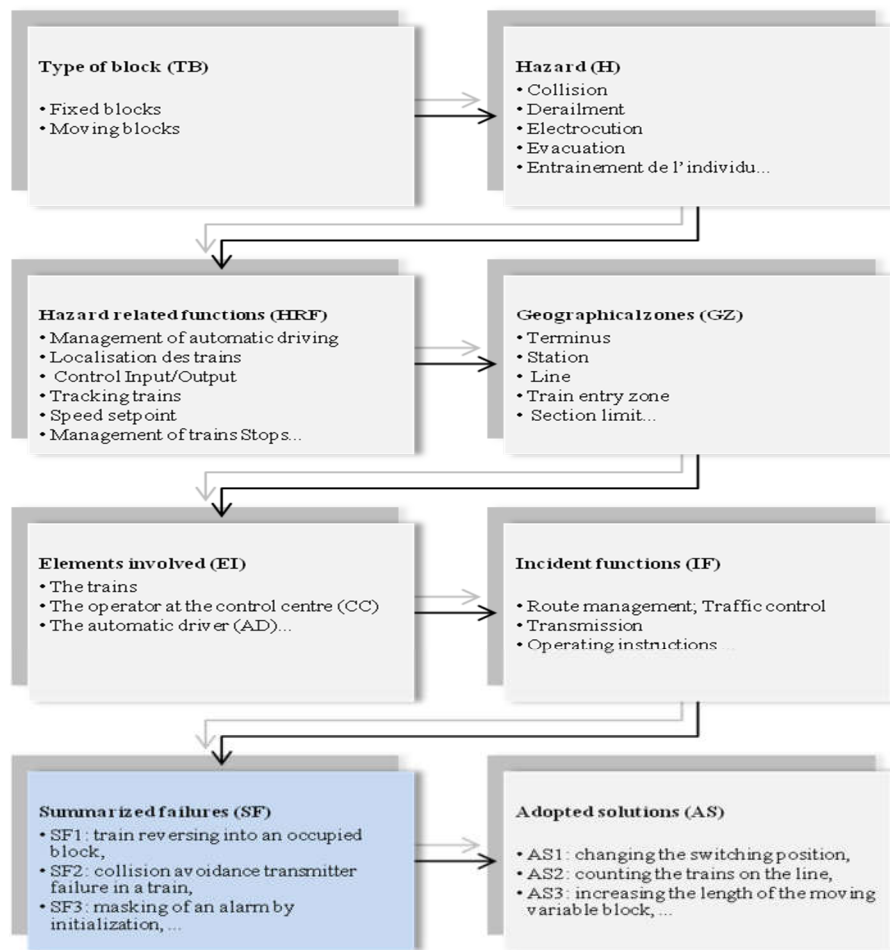


Figure 3: List of the parameters which relate to accident scenario

from a set of historical examples (or scenarios). The specification of the properties required by the learning system and a review of the literature has led us to choose the CHARADE mechanism. CHARADE's ability to generate automatically a system of rules, rather than isolated rules, and its ability to produce rules in order to develop SF recognition functions make it of undeniable interest. A sample of some rules generated by CHARADE is given below. These relate to the "initialization sequence" class (Figure 4).

```
If elements_involved = mobile_operator,
    incident_functions = instructions
    elements_involved = operator_in_CC
    elements_involved = AD_with_redundancy,
    hazard_related_functions = train localization,
    geographical_zones = terminus.
Then Summarized Failures = SF11: invisible element on the zone of completely automatic driving
```

Figure 4: A sample of some rules generated by CHARADE

9. Deduction of SFs That Are to Be Considered in the Manufacturer's Scenario

Headings During the previous stage the CHARADE module created a system of rules on the basis of the learning examples. The SF deduction stage requires a preliminary phase during which the rules which have been generated are transferred to an expert system in order to construct a scenario evaluation knowledge base. This evaluation knowledge base contains the following [1], [5]:

- The base of rules, which is split into two parts: a current base of rules which contains the rules which CHARADE has generated in relation to a class which tool has suggested at the instant t and a store base of rules, which consists of the list of historical bases of rules. Once a scenario has been evaluated, a current base of rules becomes a store base of rules,
- The base of facts, which contains the parameters which describe the manufacturer's scenarios which are to be evaluated.

The scenario evaluation knowledge base which has been described above (base of facts and base of rules) is exploited by forward chaining by an inference engine and generates the summarized failures (SFs) which must enter into the description of the scenario which is to be

evaluated. In the example we are considering the expert system deduced the failure SF19. The result of the deduction is given below (Figure 5).

```
@@ 23/09/2016
moving_block
collision
management_of_automatic_driving
train_monitoring
initialization
terminus
operator_at_CC
ad_without_redundancy
instructions
DEDUCTION:
Summarized failure = SF19: Silent train
```

Figure 5: Example result of deduction by the expert system

Conclusions

Expertise in a domain is not only possessed by experts but is also implicitly contained in a mass of historical data which it is very difficult for the human mind to summarize. One of the objectives of machine learning is to extract relevant knowledge from this mass of information for explanatory or decision making purposes. However, learning from examples is insufficient as a means of acquiring the totality of expert knowledge and knowledge acquisition is necessary in order to identify the problem which is to be solved and to extract and formalize the knowledge which is accessible by customary means of acquisition. In this way each of the two approaches is able to make up for the shortcomings of the other. In order to improve the process of expertise transfer, it is therefore beneficial to combine both processes in an iterative knowledge acquisition process. Our approach has been to exploit the historical scenario knowledge base by means of learning with a view to producing knowledge which could provide assistance to experts in their task of evaluating the level of safety of a new system of transport.

This paper describes our contribution to improving the usual safety analysis methods used in the certification of railway transport systems. The methodology is based on the complementary and simultaneous use of knowledge acquisition

and machine learning. The purpose is contributed to the generation of new accident scenarios that could help experts to conclude on the safe character of a new rail transport system. The safety analysis knowledge which has been acquired at the present time is far from representative of the domain and needs to be supplemented by other collision hazard related scenarios and extended to include several other accident hazards (derailment, electrocution, etc.). Initially, it is necessary to construct an integrated version of a prototype in order to finalize the results of the demonstration model.

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