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A hybrid reasoning system for the prevention of rail accidents

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ABSTRACT: *This article 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. To demonstrate the feasibility and soundness of the proposed approach to assist in the analysis and evaluation of railway safety, we have developed a software tool. This tool is composed of two main modules: A module for the classification and capitalization of historical accident scenarios and a module for evaluating the completeness and consistency of the new scenarios proposed by the manufacturer of the transport system. The first classification module is an inductive, incremental and interactive learning system. The second evaluation module, which is based on the use of a rule-learning system, aims to provide experts with suggestions of potential failures which have not been considered by the manufacturer and which are capable of jeopardizing the safety of a new rail transport system. In contrast to traditional failure Diagnosis Systems, the developed software tool can be seen as an aid which reveals potential risk during the design stage of rail system.*
Keywords: *Machine learning, knowledge acquisition, expert systems, railway safety, risk assessment*

I. INTRODUCTION

One of the research activities which is currently in progress at the French institute lFSTTAR relates to the certification of automated public transport systems and the safety of digital control systems. Our study took place within this context and aimed to design and create a software tool to aid safety analysis for automated people movers in order to appraise the suitability of proposed protection equipment. The purpose of this tool is to evaluate the completeness and consistency of the accident scenarios which have been put forward by the manufacturers and to play a role in generating new scenarios which could be of assistance to experts who have to reach a conclusion regarding the safety a new rail transport system. Experts may find it very difficult to describe in clear terms the stages of reasoning which they go through in order to make decisions. Such a description requires experts to undertake a long process of thought which will enable them to explain the unconscious aspect of their activities. The success of a knowledge based system (KBS) project depends on this difficult and sometimes painful task. In view of the complexity of the knowledge of experts and the difficulty which they have in explaining their mental processes there is a danger that the extracted knowledge will be either incorrect, incomplete or even inconsistent. A variety of research in Artificial Intelligence (AI) in an attempt to understand this problem of the transfer of expertise. Research is currently taking place in two major independent areas:

- Knowledge acquisition [1], which aims to define methods for achieving a better grasp of the transfer of expertise. These methods chiefly involve software engineering and cognitive psychology;
- Machine learning [2], which involves the use of inductive, deductive, abductive or analogical techniques in order to provide the KBS with learning capacities

In order to develop a KBS which aids in safety analysis we combined these two approaches and used them in a complementary way [3].

II. ASSESSMENT OF RAILWAY TRANSPORT SAFETY

As part of its missions of expertise and technical assistance, IFSTTAR evaluates the files of safety of guided transportation systems. These files include several hierarchical analysis of safety such as the preliminary analysis of risks (PAR), the functional safety analysis (FSA), the analysis of failure modes, their effects and of their criticality (AFMEC) or analysis of the impact of the software errors. These analyses are carried out by the manufacturers. It is advisable to examine these analyses with the greatest care, so much the quality of those conditions, in fine, the safety of the users of the transport systems. Independently of the manufacturer, the experts of IFSTTAR carry out complementary analyses of safety. They are brought to imagine new scenarios of potential accidents to perfect the exhaustiveness of the safety studies. In this process, one of the difficulties then consists in finding the abnormal scenarios being able to lead to a particular potential accident. It is the fundamental point which justified this work.

The commissioning authorization for the transport system is granted by the relevant State departments on the basis of the certification dossier. Certification is the official recognition that a function, a piece of equipment or a system complies with a set of national or international regulations. State departments generally make use of external audits or expert bodies such as IFSTTAR in order to draw up certification notices. IFSTTAR has as its main objectives the examination and evaluation of the development, validation and approval methods of the system. This process consists of devising new scenarios for potential accidents to ensure that safety studies are exhaustive. One of the difficulties involved in this process is finding abnormal scenarios which are capable of generating a specific hazard. This is the fundamental issue which inspired this study. There is a hierarchy of several ranked safety processes which are accepted by INRETS and conducted by the manufacturer in order to identify hazardous situations, potential accidents, hazardous units or equipment and the severity of the consequences which would result. These processes are as follows [4]:

– Preliminary hazard analysis (PHA),
– Functional safety analysis (FSA),
– Hardware safety analysis (HSA)
– Software safety analysis (SSA)

Modes of reasoning used in security analysis (inductive, deductive, by analogy ...) and the nature of security knowledge (incomplete, evolving, empirical, qualitative ...) confirm that a conventional computer solution is inadequate and that the use of techniques of artificial intelligence (AI) seems most appropriate. Indeed, despite the undeniable interest of the usual methods of analysis and safety assessment, completeness of the analysis is essentially based on the expertise, intelligence and intuition of the human expert. A careful study of the mechanisms of the expert reasoning, strategies and heuristic problem solving, shows that it mainly involve symbolic data, scalable, qualitative and makes simultaneous use of inductive, deductive, by analogy type inference ...

This is what led us to use Artificial Intelligence techniques for therefore enhance conventional methods for safety analysis. For our work, we used mainly three aspects of the field of AI: knowledge acquisition (KA), machine learning (ML) and knowledge based systems (KBS). The development of the knowledge base of a KBS requires the use of techniques and methods of KA to collect organize and formalize knowledge. The KA did not, efficiently extract some expert knowledge of security analysis by itself. Also, the combined use of KA and ML showing up as a very promising solution. The approach used to develop all the tools to analyze security involves two major activities:

• Retrieve, formalize and archive insecurities in order to build a library of test cases covering the whole problem. This activity has required the use of knowledge acquisition,
• Exploit archived historical knowledge in order to identify expertise in security analysis may help experts judge the completeness of the analysis of security given by the manufacturer. The approaches used to identify this second activity are based on the use of machine learning methods.

Our approach is to operate by learning all the basics of historical knowledge on accident scenario in order to produce knowledge that could help certification experts in their task of assessing the degree of safety of a new transport system.

III. KNOWLEDGE ACQUISITION OF SAFETY

The Knowledge acquisition was recognized as a bottle neck from the first appearance of expert systems, or more generally knowledge based systems. 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: 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. This time-consuming and difficult process is nevertheless fundamental to the creation of an effective knowledge base. 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). In summary, KA may be defined as being those activities which are necessary in order to collect, structure and formalize knowledge in the context of the design of a KBS. The work which has been conducted by Aussenac [1], Dieng [5] and Benkirane [6] provide a fairly full description of variety of existing methods and tools. In our feasibility study of a KBS for aid in safety analysis we adopted the conceptual approach suggested by Benkirane [6]. This is a particularly complete and structured model in that it considers four dimensions: the phases of the development of the KBS, the stages of knowledge extraction, the environment of the problem and human factors. By applying this model to safety the domain of expertise was accurately defined and its fundamental concepts listed. From this also emerged a generic model for representing accident scenarios. 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 for the French rail systems: VAL, POMA 2000, MAGGALY and Northern TGV systems and the know-how of experts IFSTTAR. However, in spite of the large number of knowledge extraction sessions (approximately thirty) and the utilization of several knowledge collection techniques (interviews, questionnaires, protocol analysis, conceptual classification, etc.) the knowledge acquisition model did not permit the detailed identification of the mechanisms involved in the reasoning of experts, or the strategies and heuristic approach which they use in problem solving. This difficulty is essentially due to the novelty and complexity of the field and the intuitive, evolving and creative nature of the reasoning mode employed by experts. We shall present below the results of knowledge acquisition as they relate to analyzing and characterizing an accident scenario (figure 1).

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 (figure 1). 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 we have adopted the formalism of Petri Nets. The form adopted for the static description is that of a list (figure 1) in which several essential descriptive parameters are described in attribute/value terms. Very schematically, guideway 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 ACASYA tool finds and then exploits shared bricks in order to deduce the class to which a new scenario belongs (module CLASCA) or evaluate its completeness (module EVALSCA).

A survey of state of the art research in the domain of knowledge acquisition made it possible to select a method for developing a KBS for aid in the analysis of safety for automated terrestrial transport systems. This method showed itself to be useful for extracting and formalizing historical safety analysis knowledge (essentially accident scenarios) and revealed its limits in the context of the expert safety analysis, which is particularly based on intuition and imagination. In general, current knowledge acquisition techniques have been designed for clearly structured problems.

They do not tackle the specific problems associated with multiple areas of expertise and the coexistence of several types of knowledge and it is not possible to introduce the subjective and intuitive knowledge which is related to a rapidly evolving and unbounded field such as safety. Although cognitive psychology and software engineering have produced knowledge acquisition methods and tools, their utilization is still very restricted in a complex industrial context. In our opinion, machine learning can make a contribution by supplementing and reinforcing conventional knowledge acquisition resources. The following section demonstrates the benefits of machine learning in the development of a knowledge base.

List of attributes	List of possible values	
Type of block	Fixed block	
	Moving block	
Hazards	Collision	
	Derailment	
	Poorly controlled emergency evacuation	
	Falling in a vehicle	
	Falling onto the way	
	Person dragged along the way	
	Electrocution	
	Shock during door closure	
Hazards related functions	Management of automated driving	
	Train localization	
	Control of entrance and exit	
	Train monitoring	
	Management of direction control	
	Speed instruction	
	Management of train stopping	
	Platform/Way Safety	
	Full control/High Voltage permission	
	Redundancy switching	
	Initialization	
	Manual driving	
	Alarm management	
	Evacuation	
	Pushing	
	Protection of routes	
	Traction/braking	
Geographical zones	Terminus	
	Station	
	Line	
	Train entry	
	Section limit	
Elements involved	Number of trains`	
	CC operator	
	Mobile operator	
	AD with redundancy	
	AD without redundancy	
Incident functions	Route management	
	Traffic control	
	Instructions (consistency, vigilance)	
	Communication (transmission)	
Summarized failures	SF52	Stationary train on way
	SF24	Permanent traction failure
	SF9	Entering occupied block
	SF11	Invisible element in the zone of completely automatic driving
	SF10	Erroneous re-establishment of Safety frequency/High voltage
Adopted solution	AS51	Check the traction current during emergency braking, open circuit breakers if necessary

Fig (1): List of the parameters which relate to an example of a accident scenario.

IV. MACHINE LEARNING FOR AID TO ACCIDENT RISK ASSESSMENT IN RAILWAYS

Learning is a very general term which describes the process by which human beings or machines increase their knowledge. Learning therefore involves reasoning: discovering analogies and similarities, generalizing or particularizing an experience, making use of previous failures and errors in subsequent reasoning. The new knowledge is used to solve new problems, to carry out a new task or improve performance of an existing task, to explain a situation or predict behavior. The design of knowledge acquisition aid tools which include learning mechanisms is essential for the production and industrial development of KBSs. This discipline is regarded as being a promising solution for knowledge acquisition aid and attempts to answer certain questions: how can a mass of knowledge be expressed clearly, managed, added to and modified? In the view of Ganascia [7] machine learning is defined by a dual objective: 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. Three types of problems are raised for each of the main learning techniques [2]. The first of these is grouping (which is termed classification in data analysis): given a certain mass of knowledge, how is it possible to discover links between the different items in order to group them into meaningful and simpler sub-groups? The second problem (discrimination) is that of learning classification procedures: with a given set of examples of concepts, how is it possible to find a method which provides effective recognition of each concept? The third problem is that of generalization: how is it possible, on the basis of concrete examples of a situation, to find a formula which is sufficiently general to describe the situation in question and how is it possible to explain the descriptive ability of this formula?

After examining a variety of methods, techniques and systems for machine learning we decided to select the CHARADE system [7] in order to produce failure recognition rules. It also led us to appreciate the need to design a new system, known as CLASCA for classifying accident scenarios. This choice was based on the identification of requirements, the characteristics of the acquired knowledge and on the specification of the performance which was expected from the learning process. The CLASCA and CHARADE systems supplement each other in order to develop the ACASYA safety analysis tool.

V. "ACASYA": FUNCTIONAL SAFETY ANALYSIS AID SYSTEM

The ACASYA system [3] is based on the combined utilization of knowledge acquisition techniques and machine learning. The tool has two main characteristics: it possesses the incremental aspect which is essential in order to achieve a gradual improvement in the knowledge the system gathers and man/machine co-operation which allows experts to correct and supplement the knowledge. Unlike the majority of decision making aid systems which are intended for a non-expert user this tool is designed to co-operate with experts in order to assist them in their decision making. The organization of ACASYA is such that it reproduces as mauch as possible the strategy which is adopted by experts. Summarized briefly, safety analysis involves an initial recognition phase during which the scenario in question is assimilated to a family of scenarios which is known to the expert. This phase requires classes of scenarios to be defined. In a second phase the expert evaluates the scenario in an attempt to evolve unsafe situations which have not been considered by the manufacturer. These situations provide a stimulus to the expert in formulating new accident scenarios. As is shown in figure 2 this organization consists of four main modules. The formalization module deals with the acquisition and representation of a scenario and is part of the knowledge acquisition phase. The three other modules, CLASCA, EVALSCA and GENESCA, in accordance with the general principle which has been laid down above, deal with the problems associated scenario classification, evaluation and generation.

In more formal terms, the methodology of safety analysis aid is based on two models: a generic accident scenario representation model, which is based on a static and a dynamic description of a scenario and a model of the implicit reasoning of the expert which involves three major activities, namely the classification, evaluation and generation of scenarios. The main purpose of the study is to combine these two models and make use of learning techniques in order to make the expert model as explicit as possible so that the expert process can be reproduced. The first level relates to finding the class to which a new scenario which has been suggested by the manufacturer belongs. The purpose behind this is to provide the expert with historical scenarios which are partially or completely similar to the new scenario.

This mode of reasoning is analogous to that which experts use when they attempt to find similarities between the situations which have been described by the manufacturer's scenarios and certain experienced or envisaged situations involving equipment which has already been certified and approved. Classification of a new scenario involves the two following stages:

• A characterization (or generalization) stage for constructing a description for each class of scenarios. This stage operates by detecting similarities within a set of historical scenarios in the HSKB which have been pre-classified by the expert in the domain;

• A deduction (or classification) stage to find the class to which a new scenario belongs by evaluating a similarity criterion. The descriptors of the new scenario (static description) are compared with the descriptions of the classes which were generated previously.

This initial level of processing not only provides assistance to the expert by suggesting scenarios which are similar to the scenario which is to be dealt with but also reduces the space required for evaluating and generating new scenarios by focusing on a single class of scenarios Ck.

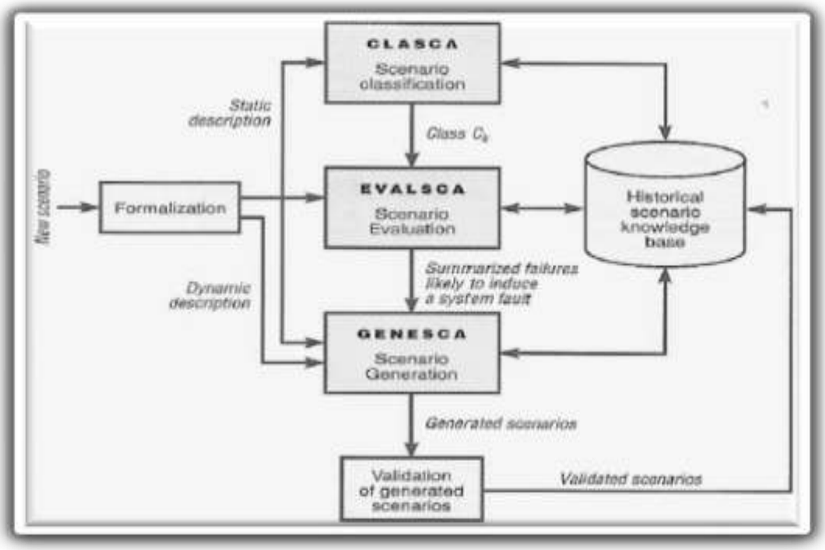

Fig (2): Functional organization of the ACASYA system.

"CLASCA": The first level of processing considers the class which CLASCA has deduced that the scenario belongs in order to evaluate the consistency of the manufacturer's scenario. The evaluation approach is centered around the summarized failures (SFs) which are involved in the manufacturer's scenario. The evaluation of a scenario of this type involves the two modules below:

• A mechanism for learning rules CHARADE [7] which makes it possible to deduce SF recognition functions and thus generate a base of evaluation rules;

• An inference engine which exploits the above base of rules in order to deduce which SFs are to be considered in the manufacturer's scenario.

CHARADE 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 → 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 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 → d4 is obtained.

"EVALSCA": The purpose of the EVALSCA module is to compare the list of SFs which are suggested in a manufacturer scenario to the list of stored historical SF in order to stimulate the formulation of hazardous situations which have not been anticipated by the manufacturer. This evaluation task draws the attention of the expert to any failures which have not been considered by the manufacturer and which might jeopardize the safety of the transport system. It may thus promote the generation of new accident scenarios.

"GENESCA": The two levels of processing which have been described above make use of the static description of the scenario (descriptive parameters). They are supplemented by a third level which makes use of the static description and the dynamic description of the scenario (the Petri model) and three reasoning mechanisms, namely, induction, deduction and abduction. Generation of a new scenario is based on injecting an SF which the previous level has defined as being plausible into a specific sequencing of the change in marking of the Petri net.

In view of the scale of the problem the design and construction of the demonstration model of the ACASYA system concentrated on the first two levels of processing (classification and evaluation of scenarios). The feasibility study of the ACASYA system which is applied in the context of safety involved the construction of a model. In order to evaluate this model we tested its performance on approximately sixty accident scenarios relating to a collision hazard which have been collected so far. The utilization of ACASYA requires six stages to be carried out,

the first four of which are performed by CLASCA and the last two by EVALSCA:

- Knowledge acquisition,
- Learning descriptions of scenario classes,
- Classification of a new scenario,
- Construction of the base of learning examples centered around the SFs which are involved in the description of the class to which the new scenario belongs,
- Learning the SF recognition functions,
- Deduction of which SFs are to be considered in the scenario which is to be evaluated.

The first stage involves the collection of safety analysis knowledge with respect to transport systems. 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. The second induction stage of descriptions 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. The description of a class is further enriched by taking into account the associated summarized failures which are involved.

These SFs will subsequently be exploited in order to develop the base of learning examples. In this stage a new example of a scenario is assigned to an existing class Ck. 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. 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 output by CLASCA 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 learning mechanism. The base is refreshed each time the classes suggested by CLASCA are updated. This phase of learning attempts, using the base of 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. What is involved here is logical dependence, which can be expressed in the following form: 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 from a set of historical examples (or scenarios). The specification of the properties required by the learning system and a review of the literature have 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.

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:

– 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 CLASCA 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 which must enter into the description of the manufacturer's scenario which is to be evaluated. In the example we are considering the expert system deduced the failure SF19 (figure 3).

The result of the deduction is given below. The plausible SFs which the expert system has deduced are analyzed and compared to the SFs which have actually been considered by the manufacturer. One or more SFs which jeopardize the safety of the transit system and which have not been considered by the manufacturer during the design of protection equipment may emerge from this comparison. The above suggestion may assist in generating unsafe situations which have not been foreseen by the manufacturer (figure 3).

```
        moving_block
        collision
        management_of_automatic_
           driving
        train_monitoring
        initialization
        terminus
        operator_at_cc
        ad_without_redundancy
        instructions

DEDUCTION:
        Summarized failure = SF19
           (Silent train)
```

Fig (3): Example deducting summarized faults (SFs) by the expert system

VI. CONCLUSION

Examination of the Rail Transportation Safety has shown that the process of transferring expert knowledge to a machine is complex and rarely studied and that the bottle-neck in the development of knowledge based systems (KBS) is not restricted solely to the extraction phase but also involves the characteristics and formalization of knowledge and collaboration between experts and cognitive scientists. There is generally speaking no scientific explanation which justifies this compiled expertise. The experts themselves are not always conscious of this knowledge, which can be difficult to understand for someone who is new to the field or even sometimes hard to express by means of language. Transcribing verbal (natural) language into a formal language which can be interpreted by a machine often distorts the knowledge of the expert. 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. 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 [8].

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