Constructing a diagnostic knowledge base for building faults = creation d'une base de connaissances pour le diagnostic des desordres du bâtiment

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CONSTRUCTING A DIAGNOSTIC KNOWLEDGE BASE FOR BUILDING FAULTS

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KEYWORDS

building diagnosis, artificial intelligence, knowledge based systems, machine learning, knowledge acquisition

ABSTRACT

A computer system has been developed to build a knowledge base for automatic diagnosis of building faults. The system is being deployed by an architectural firm and has been designed to accommodate their method for surveying building problems. This knowledge-acquisition assistant writes rules for diagnosing problems and verifies the logical consistency of the knowledge base as it grows.

Numerous prototype "expert systems" have been developed for the construction industry . Many of these systems have been for diagnosing building faults. Typically, they have been programmed using ad hoc methods of coding the knowledge of a specific field into the required form for the system. Either experts themselves have built entire systems, or knowledge engineers have used personal interview techniques. These strategies limit the size of the knowledge base and its future expansion. Typically, only the knowledge base authors will be able to add to the rule base. At a point during its development the rule-base becomes too complex to augment without developing logical inconsistencies, and the systems remain prototypes without ever being used.

At IRC, after numerous knowledge base system prototypes were developed using ad hoc methods, these rule base authoring problems and quality assurance problems prompted the development of a rule authoring assistant. This system is being applied by a firm actively engaged in building a knowledge based system to aid with the diagnosing of building faults. The major problem with building a large and growing system is maintenance of the knowledge base by the users, while assuring the logical consistency of the rule set.

The system comprises an inductive rule generation module and a rule verification module tied to a rule editor. These three components are used to formulate the rules in the knowledge base. To perform a diagnosis, the accepted rules are used to help diagnose the next case (or expert system shell). Each subsequent diagnostic case is used to add rules and subsequently the rule base is checked for consistency.

This type of approach constrains the form of reporting building faults but allows many authors to co-operate in the building of a rule base. The result is a consistent syntax for diagnosis and an expanding rule base for a self-automating building diagnostic system.

CRÉATION D'UNE BASE DE CONNAISSANCES POUR LE DIAGNOSTIC DES DÉSORDES DU BATIMENT

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MOTS CLÉS

diagnostic du bâtiment, intelligence artificielle, systèmes à base de connaissance, apprentissage (d'une machine), saissie de connaissances

RÉSUMÉ

On a mis au point un système informatique permettant de créer une base de connaissances pur le diagnostic automatique des désordres du bâtiment. Ce système, confié à une firme d'architectes, est conçu de façon à utiliser leur méthode d'examen des problèmes du bâtiment. Cet assistant saisisseur de connaissances écrit des règles de diagnostic des désordres et vérifie la cohérence logique de la base de données à mesure de son développement.

On a construit de nombreux prototypes de "systèmes experts" destinés à l'industrie de la construction. Nombre de ces systèmes servent au diagnostic des désordres du bâtiment. De façon générale, ils ont été programmés à l'aide de méthodes spéciales consistant à coder les connaissances d'un domaine donné sous la forme exigée par le système. Dans certains cas, les experts eux-mêmes ont créé des systèmes complets, dans d'autres, les cogniticiens ont utilisé les techniques d'entrevues personnelles. Or ces stratégies limitent le volume de la base de connaissances et son expansion future. Habituellement, seuls les auteurs de la base de connaissances sont en mesure d'ajouter à la base de règles. A un moment donné de son développement, cette base devient très difficile à enrichir sans que n'apparaissent des incohérences logiques, et les systèmes ne dépassent pas le stade du prototype, sans jamais être utilisés.

Après la mise au point de nombreux prototypes de systèmes à base de connaissances à l'aide de méthodes spéciales, ces problèmes d'ajout à la base de règles et des problèmes de gestion de la qualité ont incité l'IRC à créer un assistant rédacteur de règles. Ce système est actuellement utilisé par une firme travaillant à la constitution d'un système à base de connaissances destiné à faciliter le diagnostic des désordres du bâtiment. La principale difficulte que pose la création d'un vaste système en expansion constante consiste à assurer à la fois la mise à jour de la base de connaissances par les utilisateurs et la cohérence logique de la série de règles.

Le système en question comporte un module de production de règles par induction et un module de vérification des règles connecté à un éditeur de règles. Ces trois éléments servent à formuler les règles de la base de connaissances. Pour établir un diagnostic, on utilise les règles acceptées pour faciliter le diagnostic du cas suivant (ou coquille vide). Chaque cas de diagnostic subséquent sert à ajouter des règles; on vérifie par la suite la cohérence de la base de règles.

Cette façon de procéder impose des contraintes quant au mode de signalement des désordres du bâtiment mais il autorise la collaboration à la création d'une base de règles. Il en résulte une syntaxe cohérente de diagnostic et une base de règles en expansion assurant un système de diagnostic du bâtiment qui s'automatise lui-même.

INTRODUCTION

Numerous knowledge based system prototypes have been developed for the building industry. Most of these systems have been for diagnosing building problems. Typically, these prototypes focus on a particular aspect of the building. Systems have been developed for solving window problems[1], compressor problems for mechanical systems[2], rising damp problems[3], water penetration[4], and masonry failure[5]. The majority of these prototypes are rule based systems and follow a conventional pattern of knowledge acquisition; either the experts themselves have built the systems, or knowledge engineers have constructed the rule base using various interview techniques[6]. These knowledge acquisition techniques limit the size of prototype systems and their extensibility.

A project undertaken by an architectural firm emphasized the problems of developing a large knowledge base for building diagnosis. The ambitious nature of the project, automatic diagnosis of most building problems, served to illustrate key issues. Several experts would be needed to construct such a knowledge base. The knowledge base would continue to grow as new illnesses and relationships were discovered. A systematic method of recording data would be required and a pathology linking data to specific buildings and building illnesses would be required.

To aid in the generation of a working knowledge base, the development of a rule authoring assistant was undertaken. A methodology was developed for the construction of the knowledge base. This methodology was based on incremental expansion of a knowledge base, coupled with rule base verification after each step. A computer system was built to assist in the construction of a knowledge based system using the architectural firm's diagnostic techniques. Rules were created by an author and were generated from data using machine learning techniques. The system consists of three components, namely an interface and editor module linking an inductive rule generation system and a rule verification system that maintains logical consistency.

DIAGNOSING BUILDING PROBLEMS

The diagnosis of building problems is analogous to the diagnosis of medical illnesses. Symptoms and signs are recorded by the diagnostician. For the purposes of this discussion, symptoms (reported by the user) will be combined with signs (objective physical evidence including measurements) into one category called symptoms. The symptoms are effectively organized and a diagnosis is made. Diagnosis must be linked to the prediction of future events, therefore a prognosis is required. The prognosis for the patient may be good or poor. A decision whether or not to intervene is based on the prognosis. A treatment or therapy may be prescribed if a decision is made to intervene.

Building diagnosis differs from medical diagnosis in that there is no well defined pathology in building science. Information about building illnesses has not been gathered and organized as in the medical field. Building science lacks the good models on which proper diagnostic procedures must be founded. A syntax needs to be developed to relate the problem (illness) to the outward manifestations (symptoms) and their causes. A taxonomy is also needed to ensure that symptoms of problems, building related symptoms, structures, materials, and diagnostic results are recorded consistently. Currently building diagnosis is more of an art than a science[7]. There are attempts to establish a building pathology for the correct diagnosis of building illnesses[8].

A Manual Method

Building surveys are performed by experts with many years of field experience. Generally these experts rely on inspection and non-destructive testing techniques to establish a diagnosis and a prognosis. The process begins with a walk through inspection. During this inspection the expert would record various sensory input, making notes, taking photographs or video tapes, and perhaps perform some non-destructive tests, such as measuring moisture contents or ultrasonic measurements. An important part of this step is to organize the information collected in a systematic and comprehensive manner. At this point a mental model is built that combines the condition of the component systems, the symptoms, and the related causes. Eventually all the information would be deductively pieced together and the illness identified.

An Automated Method

The current method of building diagnostics requires an expert practitioner. Experts are scarce, and requiring them to perform a time consuming analysis of a building is expensive. An automated method was proposed by an architectural firm to reduce the amount of expertise needed to perform a building diagnosis and document the models used by experienced practitioners. The walk through method would be retained; however, a rigid syntax would be imposed on the surveyor. The architect or technologist would encode relevant building data using predefined codes. These codes would describe the building systems, construction materials, observed symptoms, orientation, cause and illness (if possible). Quantity of and percentage of affected materials would also be recorded to allow cost estimates for remedial actions to be generated.

Using a series of predefined alphanumeric codes, a building surveyor would systematically inspect every aspect of the building, recording the observations using tape recorders or coding forms. Descriptive text or mental notes would be recorded as "memos" to be used later during the data reduction phase. The records obtained in the field would be transcribed from the tape or coding forms and entered into a popular micro-computer database program[9] for analysis. The collected data describe a building and its problems as successively more detailed alphanumeric code. An expert would then review this description of the building and attempt a diagnosis. Eventually this phase would also be automated, by developing a knowledge based system to use the database files created by the field surveys. Diagnoses and prognoses would be generated automatically. Prescriptions could then be meted out based on the relative costs of the remedial actions.

CONSTRUCTING A KNOWLEDGE BASE

The domain of building illnesses is quite large and the development of a knowledge based system to solve these problems is an ambitious task. In view of the complexity of the problem, the number of experts required to span the domain, and resource limitations, a non-traditional approach to knowledge acquisition was developed. A methodology for the construction of the knowledge base was proposed. A rule authoring assistant was constructed to facilitate the generation of rules.

Rule generation took place using two techniques. Rules were explicitly written by experts if the underlying models they used could be articulated. Rules were also generated from the records of existing building surveys. The records contain a condensed version of a diagnostic session. The expert's knowledge was captured in the database records. This knowledge was extracted from the records and formed into rules.

The following is a scenario for the knowledge base development. A file containing the results of a building survey or surveys would be run through a rule generator. The rules would be reviewed by experts and modified if necessary. The rules would then comprise the working knowledge base. New rules would be generated manually or automatically by the processing of other building survey files. The knowledge base would be built incrementally. Rules would be based on a growing body of knowledge.

The continued addition of rules by various human experts and the rule generator allow for the introduction of logical inconsistencies in the rules. Duplicate or superfluous rules could also be added. To resolve potential inconsistencies the rule authoring assistant contains a verification package. As new rules are added the verification package tests these new rules against the existing knowledge base. Problems are reported, and the experts edit the knowledge base accordingly. The knowledge base construction process is shown in Figure 1.

AUTOMATED RULE GENERATION

Rule generation was accomplished using variations of two known methods of machine induction. In this context machine induction or machine learning will refer to the problem of learning from examples[10]. An example set is processed by a learning algorithm. The algorithm attempts to create generalizations from the example set. One method was based on Quinlan's[11] ID3 algorithm while the other method was based on Michalski's[10] AQ11 algorithm. A third module in the rule authoring assistant contains a commercial data analysis/knowledge acquisition[12]. This statistical software package is based on the work of Sonquist[13], Brieman[14], Quinlan[11], and Hunt[15]. The system simulates the steps taken by a skilled data analyst to identify important rules and relationships among variables in a data set. This tool was used to identify relevant attributes in the data set prior to using the rule induction algorithms, and to provide a statistical base line for rule generation.

Data files were provided by the architectural firm for test purposes. An example of a data file is shown in Figure 2(a). Performance of statistical analysis tools and two different learning algorithms were compared. The small size of the files used did not support meaningful statistical relationships. That in itself indicated that caution be used in interpreting the results. The formal, statistical methodology was able (in addition to its "best fit" methodology) to classify attributes on user-specified attributes, providing useful relationships. This type of analysis, in some cases, produced more generalized rules than those produced by the rule induction algorithms.

In a direct comparison of the ID3 type and AQ11 based programs the following observations were made. The ID3 algorithm, extended to handle numbers, proved better in handling numerical attributes than its AQ11 counterpart. The ID3 type algorithm was faster by an order of magnitude than AQ11. The AQ11 based program produced rules that were more general in their nature then the ID3 based program. Most of the rules generated using AQ11 contained fewer antecedent (If) clauses and each clause generally contained fewer attributes. Both methods produced rules that completely covered the example sets used as input.

The combination of a statistical analysis package and the two machine induction algorithms provides a rich environment in which rules can be generated from data. An example of the rules generated automatically by the rule generation package is shown in Figure 2(b). The rules were generated from the data file shown in Figure 2(a) by the ID3 induction algorithm.

KNOWLEDGE BASE VERIFICATION

In small knowledge based systems that have been developed by one person it is possible to discover all faults in the rule base. It is difficult to find faults in larger and more complex rule bases. A system designed to diagnose building faults would consist of a large amount of fragmented knowledge, contributed by various sources. The iterative nature of knowledge base construction necessitates considerable interaction with experts. This interaction allows for the possibility of experts entering conflicting rules or data. To ensure that a developing knowledge base is not corrupted as it grows it must be verified and validated. Verification and validation are also needed if an application, particularly for building diagnostics, is to gain critical acceptance.

Validation techniques treat the system as a black box. Solutions arrived at by the knowledge based system are compared to those provided by experts. Adjustments are made to the system until most of the conflicts are resolved. Validation, although an essential part of acceptance testing, cannot constitute a formal proof. Knowledge base validation is an inductive method and, no matter how comprehensive the testing, cannot guarantee that future conflicts will not arise.

In a rule based system there are several possible causes of error. Rules may be in conflict, or redundant. Inference chains may be circular. Rules, inference chains or attributes may be isolated, either never invoked by the rest of the system or not able to be fulfilled.[16] An automatic verification system was constructed in order to ensure logical consistency during the development of rule bases in the rule authoring assistant[17]. The verifier does not attempt to correct logical inconsistencies. A report of the inconsistencies is generated. The problems in the knowledge base are then corrected and the verification procedure is repeated until all the inconsistencies have been removed. The verification procedures only ensure logical consistency. They check for syntactical and not semantic inconsistencies. An example of a report generated by the verifier is shown in Figure 2(c).

LEARNING TOOLS AND REAL WORLD PROBLEMS

The application of machine learning tools and knowledge based systems technology to real world problems raised several issues not perceived at the outset. The problem of building diagnostics was particularly challenging.

Problem Context

The development of the rule authoring assistant was guided by implicit axioms. These axioms were based on a database survey methodology developed by an architectural firm. The methodology is outlined above. The first axiom was that every record in the suite of completed case studies contained a complete description of an event. The second was that there were no explicit linkages between individual data records. It was also indicated that the data files would contain a large number of records.

Problems

Most of the records in the database were not complete. The records contained a complete description of the problem, but in general did not have a value for the associated causes or diagnosis. There was little or no information about the illness being experienced by the building.

The data files contained records describing problems with no known cause. All the rules generated contained a large number of antecedent conditions and a single consequent action, namely *'cause inconnu'**. The rigid system of describing faults was inadequate to relate a cause and an illness during the survey. Experts had to perform a manual diagnosis after the survey had been completed. During

* cause unknown

observation of this procedure it became apparent that the experts were explicitly linking records together to perform a diagnosis.

It was also noted that the "memo" fields included in the data files were being used in the diagnostic process. Although it was claimed that these fields were not used they were found to contain vital information such as the continuity of symptoms across systems and location information.

The files were also smaller than anticipated. The first file used contained 68 records having 31 fields, approximately half of which were empty.

Solutions

The first attempts at automated rule generation produced rules that were extremely specific in their nature. This was due to the small amount of data provided and the large number of attributes used for the trial runs. Rules contained several antecedent clauses each containing up to thirty parameters. Very little generalization was done by either rule induction algorithm. A careful selection of attributes was necessary to produce rules that actually contained some useful generalizations.

The specificity of the rules was a problem for the domain experts. Although the rules themselves were valid for the particular data set used, the experts were concerned that they were not linked in some way. A higher level of description was necessary.

Rules generated from files that were specific to a particular cause generated rules that appeared to the experts to be incomplete. One example, that of an all concrete building, generated rules that required only the symptom. The induction algorithms could not use the material parameter to discriminate between various causes because every record contained the same value for material. Consequently materials were not considered as relevant for this particular data set. This underscores the importance of human validation of automatically generated rules. Rules of this type were not generated when more complete data sets were used.

The solution to this problem was to introduce a meta-level illness parameter. By using meta-level concepts is was possible to generate a set of rules that could chain together to produce a conclusion. Rule generation would consist of multiple passes using an induction algorithm, the first pass producing conservative but accurate rules, removing redundancies from the database. The next levels of induction attempt to generalize the specific causes of building failures into more general building illnesses.

LESSONS LEARNED

The representation of building data for diagnostic purposes requires an ability to describe objects and their constituent parts. It also requires a syntax and semantics for spatial descriptions. Location and continuity information about systems and symptoms is crucial for proper diagnosis. A building pathology similar to that of human pathology is required for building diagnostics.

Learning algorithms are limited to structured problems with a well defined syntax and taxonomy. The lack of a well defined pathology for building diagnosis makes the application of machine learning tools difficult. Alternative methods of structuring data, such as a case based approach using frame based[18] models, might be used.

Issues such as geometry, spatial location, continuity of systems and symptoms were not part of the formal methodology for surveying buildings. Although it was recognized that this information was necessary it was included as text. The textual information was unstructured and therefore could not be accessed by the machine learning tools. Methods such as natural language interpretation could be used to analyse this information; however, new ways of knowledge representation, such as frames or object oriented representations, could and should also be used.

Rule based verification techniques aid in the development of knowledge bases. They quickly isolate problems and allow for an orderly growth of the knowledge base through the tenure of many authors. Research into methodologies and structured techniques for the construction of knowledge bases is required. The advancement of knowledge acquisition techniques will shorten the development time and increase the reliability and acceptance of large knowledge based systems. All of these issues are paramount for the successful commercial implementation of a knowledge based building diagnostic system.

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FIGURES

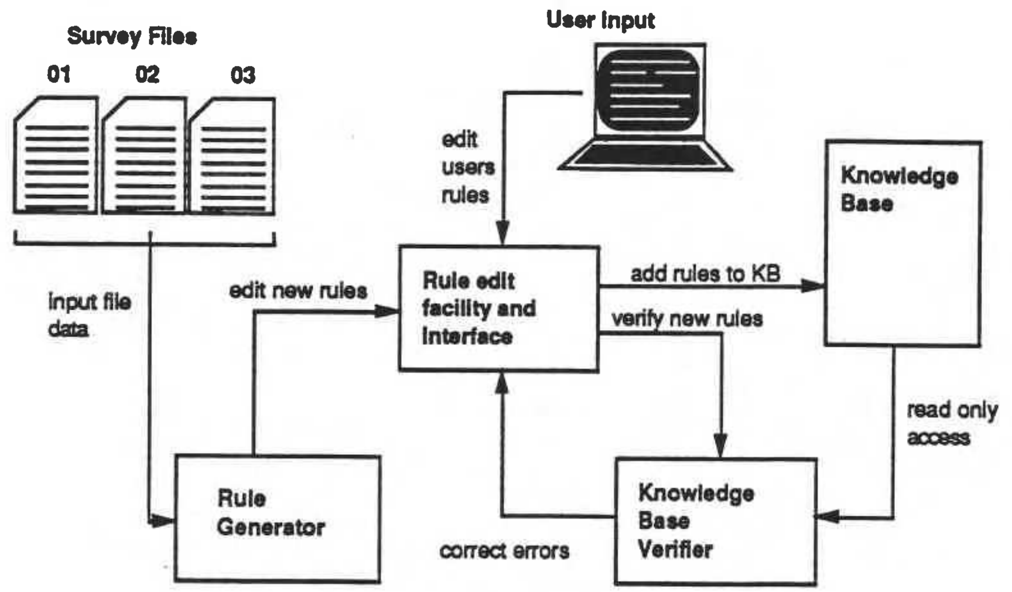

Figure 1. Process of knowledge base construction.

```
SS030304001MT075100000
SP020110000        1922I9
1922I5 9         100.00
98CA020400000
SS030304001MT075400000
SP030200000        9999A9
1922I5 9         100.00
99CA010301060
MT099100010
SP020107000        1967A5
1922I5 9 360     100.00
59CA020400000
MT084100010
SP040600000        9999A9
0   9        100.00
55CA020400000
SS030202001MT033100010
SP020107000N       1922R7
1922I9 59 270      5.00
55CA010305020
MT092200000
```

(a)

(DEFRULE PRODUIT-INAPTE This is a generated ART rule. Replace this doc string with appropos. HAL. (CODMAT IS CALFEUTRANT BASE D) => (CAUSES IS CHOIX D PRODUIT INAPTE))

(DEFRULE GEL-DEGEL This is a generated ART rule. Replace this doc string with appropos. HAL. (OR (CODMAT IS CREPI DE CIMENT)) => (CAUSES IS CYCLE DE GEL-DEGEL))

(DEFRULE POLLUANT-ACIDES This is a generated ART rule. Replace this doc string with appropos. HAL. (OR (CODMAT IS BRIQUES D) (CODMAT IS BETON

(b)

RESULTS of NOMAD'S evaluation of the rule-base.

The following logical inconsistencies were discovered:-
There is redundancy between rules PRODUIT-INAPTE and EVITA-81613-248
PRODUIT-INAPTE: IF (CODMAT = CALFEUTRANT BASE D)
THEN (CAUSES = CHOIX D PRODUIT INAPTE)
EVITA-81613-248: IF (CODMAT = CALFEUTRANT BASE D)
THEN (CAUSES = CHOIX D PRODUIT INAPTE)

There is redundancy between rules POLLUANT-ACIDES

(c)

Figure 2. Samples of (a) raw data, (b) generated rules, and (c) verifier output.