A Virtual Mining Environment for Providing Dynamic Decision Support for Building Maintenance

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Abstract. *A virtual mining environment aims to provide dynamic decision support to improve building life-cycle modelling and management. This paper presents the system architecture of a virtual mining environment, its interfaces and a user scenario. This virtual mining environment integrates data mining with agent-based technology, database management systems, object-based CAD systems, and 3D virtual environments. A system prototype has been developed and implemented to support the automated feed back for building life cycle modelling, planning and decision-making.*

Keywords. *Data Mining; Virtual Environment; Dynamic Decision Support; Building Maintenance.*

Introduction

In building maintenance, the management of building facilities is essential to achieve better reliability and availability of the equipment installed. It is important to minimize downtime of all equipments that are used as the downtime will impact on the profitability of the building itself. Maintenance activity, as part of a business process within an internal organization, contributes to the successful operation of the physical asset. The maintenance budget is a significant cost and is thus very important for the overall economic results. It has been shown that major factors contributing to construction quality problems include inadequate information and poor communication (Arditi et al. 1998; Burati et al. 1992). The detection of previously undiscovered patterns in building maintenance systems data can be used to determine factors such as the cost effectiveness and expected failure rates of assorted building materials or equipment in varying environments and circumstances. These factors are important throughout the life cycle of a building, and such information could be used in the design, construction, refurbishment, and maintenance of a building, potentially leading to a substantial decrease in cost and increase in reliability. Such knowledge is significant for saving resources in construction projects.

As the construction industry adapts to new computer technologies computerized design aids, construction, and maintenance data are all becoming increasingly available. The growth of many business, government, and scientific databases has begun to far outpace an individual's ability to interpret and digest the data. Such volumes of data clearly overwhelm the traditional methods of data analysis such as spreadsheets and ad-hoc queries. The traditional methods can create informative reports from data, but cannot analyse the contents of those reports. A significant need exists for the application of new techniques and tools to automatically assist humans in analysing the increasing volume of data for useful knowledge. The increasing use of databases to store information about facilities, their use, and their maintenance provides the background and platform for the use of data mining techniques for future projections. The current technology for facility maintenance uses databases to keep track of information and for notification of maintenance schedules. These databases are not well linked with an interactive 3D model of the building and are generally presented in tabular form.

Data Mining (DM) and Knowledge Discovery in Databases (KDD) are tools that allow identification of valid, useful, and previously unknown patterns within existing databases (Witten and Frank, 2000; Christiansson, 1998; Frawley, 1992). These technologies combine techniques from machine learning, artificial intelligence, pattern recognition, statistics, and visualization to automatically extract concepts, interrelationships, and patterns of interest from large databases. The DM and KDD techniques are capable of finding patterns in data that can assist in planning. Patterns and correlations identified from data mining existing records of maintenance and other facilities management activities provide feed back and can improve future maintenance operation decision making and inform strategic planning as well as the design of new facilities.

Most available computer tools for the building industry offer little more than productivity improvement - in the transmission of graphical drawings and textual specifications, without addressing more fundamental changes - in building life-cycle modelling and management. Virtual environments (VEs) can provide designers and facility managers with a foundation to work distributedly. Designers, building owners, facility managers and technicians can visualize and navigate the virtual building modelled in distributed virtual environments. Information can be shared in different ways depending on the way in which and the extent to which the information must be coupled.

A virtual mining environment has been developed to integrate data mining with agent-based technology, database management systems, object-based CAD systems and 3D virtual environments. This paper presents a system prototype of a virtual mining environment to provide dynamic decision support for improving building life-cycle modelling and management.

A Data Mining Approach for Dynamic Decision Support

Past experience often plays an important role in building management. "How often will this asset need repair?" or "How much time is this repair going to take?" are the types of questions that project managers face daily in their planning activities. Failure or success in developing good schedules, budgets and other project management tasks depends on the project manager's ability to obtain reliable information in order to be able to answer these types of questions. Students and young practitioners tend to rely on information that is a regional average provided by various publishing companies. This is in contrast to experienced project managers who tend to rely heavily on their personal experience.

The AEC industry is seeing explosive growth in its capabilities to both generate and collect data. Advances in scientific data collection, the introduction of bar codes for almost all commercial products, and computerization have generated a flood of data. Advances in data storage technology, such as faster, higher capacity, and cheaper storage devices, better database management systems, and data warehousing technology, have allowed the transformation of this enormous amount of data into computerized database systems. As the AEC industry is adapting to new computer technologies in terms of hardware and software, computerized building data is becoming more and more available. However, in most cases, this data may not be used, or even properly stored. Several reasons exist (Soibelman and Kim, 2002):

- Project managers do not have sufficient time to analyse the computerized data.
- Complexity of the data analysis process is beyond the capabilities of the relatively simple building maintenance systems commonly used.
- No well defined automated mechanism to extract, pre-process and analyse the data and summarize the results so that the site managers can use it.

However, there is a great deal of valuable knowledge that can be obtained from an appropriate use of this data; there is a need to analyse this increasing amount of available data and Data Mining can be applied as a powerful tool to extract relevant and useful information from this sea of data.

A Virtual Mining Environment for Providing Dynamic Decision Support

The virtual mining environment promotes real-time support and multiple team participation and involvement. The virtual mining environment can be remotely accessed synchronously by different users who will be aware of the presence of others and communicate with them. Users might mine the same or different building element based on their focus and interest. Each user might be looking at different building assets and using different mining and discovery techniques than others within the same virtual environment.

Within the virtual mining environment data-mining techniques are utilized to discover rules and patterns of useful knowledge from the maintenance records of a building to help improve the maintenance management of existing and future buildings. Although it may sound at first appealing to have an autonomous data-mining system, in practice, such a system would uncover overwhelmingly large set of patterns, and most of the patterns discovered in the analysis would be irrelevant to the user. Therefore, it is important to provide a user focused approach to mine the maintenance data of buildings.

The virtual mining environment prototype system described in this paper includes: an object oriented 3D CAD model of a building modelled in the ArchiCAD package, and a maintenance database in a standard SQL (standard query language) format. The architecture of virtual mining environment has been developed to include three agents: Interface, Maintenance and Situated agents, as illustrated in Figure 1. The roles of these agents include:

(a) The appropriate mapping between the building assets of the building model in the virtual environment is maintained by the Maintenance Agent that connects data contained within the Maintenance Database with data contained within the EXPRESS Data Manager (EDM) Database via the virtual environment, Active Worlds.

(b) Linking Data Mining techniques to building models in a virtual environment (Active Worlds) is achieved via a Maintenance Agent that accesses the maintenance database and applies its mining algorithms on it.

(c) Linking knowledge development with the building model in virtual environments is carried out by the Situated Agent that assists in improving maintenance management by providing life cycle implications as feedback whenever building assets (mechanical and electrical elements) are selected in the building model in the virtual environment (Active Worlds).

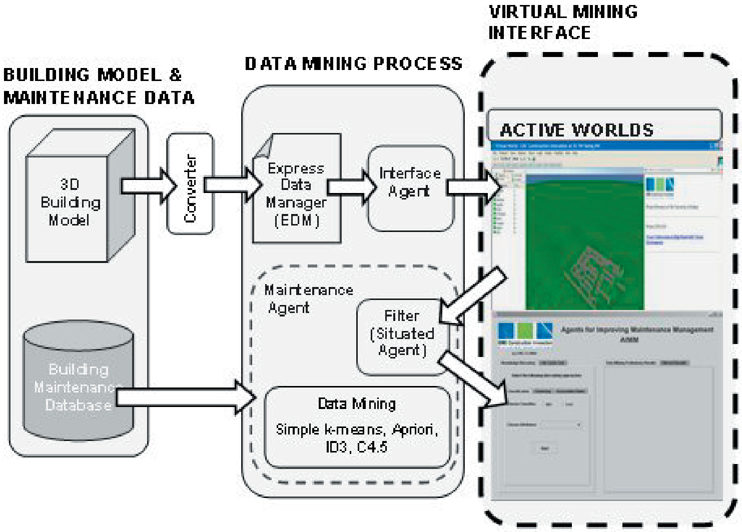

Figure 1. Architecture of the Virtual Mining Environment

Feedback of useful knowledge can be discovered by the Maintenance Agent in the application of the four data mining techniques and algorithms (Simple k-means, Apriori, ID3, and C4.5), (Witten and Frank, 2000) in order to discover various classifications of knowledge. The data mining algorithms and the link between its knowledge development and the building model in a 3D virtual environment has been fully implemented. The use of the virtual mining environment requires the utilization of the following four phases progressively:

• Phase 1: involves the manual pre-processing of data, which removes noisy, erroneous and incomplete data to derive important attributes from original raw data. For example, the raw text description of time of work orders "1/12/2001" which need to be converted to a meaningful attribute such as "month". Moreover, various "testing" algorithms are run through the maintenance data to find out the suitable data mining approaches. From Phase 1, the quality of the data can be improved.

• Phase 2: adopts the EDM interface agent developed by Maher and Gero (2002) in converting IFCs (Industry Foundation Classes) object model into a Renderware (RWX) format, so as to be presented at the virtual environment (Activeworlds). The virtual environment provides a collaborative multi-user interface and more importantly, a means for the user to walkthrough 3D object model at a real time. The user is able to navigate and select a building asset type to explore useful knowledge.

• Phase 3: instantiates the maintenance interface agent and the maintenance agent. Once the user decides to select a certain building asset the maintenance interface agent is invoked to load related data from database. The Maintenance Agent performs data mining on the selected asset type. The four mining algorithms that have been implemented in the system prototype are: clustering using "SimpleKmeans", associative rules learning in "Apriori", classification using "C4.5" and "ID3".

•Phase 4: A situated agent is activated. This is a software agent that performs post-processing of the mined results. The situated agent filters out irrelevant patterns based on the heuristic rules.

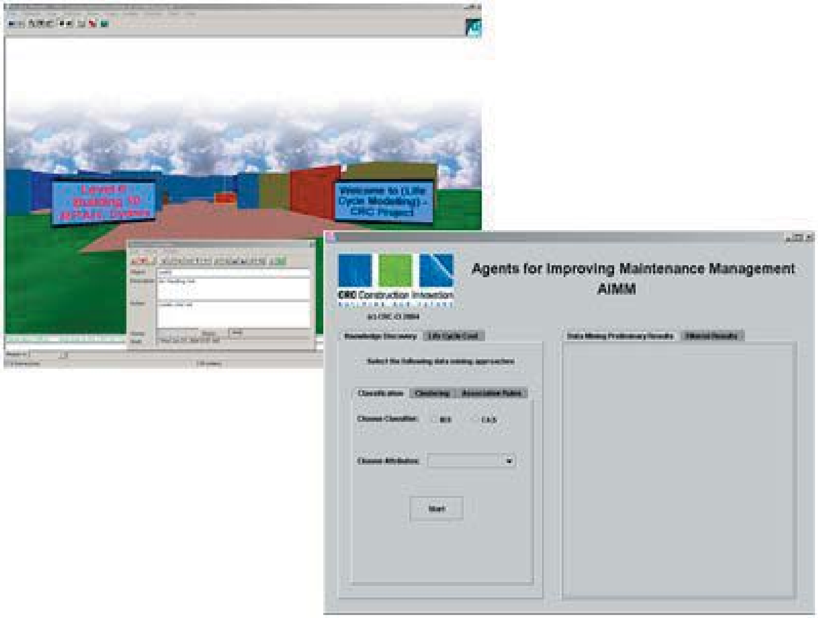

Figure 2. Selecting an asset type in Active World instantiates the maintenance interface agent.

The Virtual Mining Environment Interface and User Scenario

The user is able to navigate a 3D model within a real time virtual environment as shown in the top left of Figure 2. The user is able to instantiate the virtual mining environment prototype system by clicking on the desired building asset or component, invoking the main Maintenance Interface as shown in the bottom right of Figure 2.

Once the Interface agent is activated it pops up the Knowledge Discovery panel which has three stacked sub-panels: (I) Classification, (ii) Clustering and (iii) Associative Rules. These panels provide a range of ways for using each different algorithm. This provides the user with greater flexibility and scope since the user may test a variety of data mining approaches for each type of algorithm. On the right hand side are another two stacked panels that are dedicated to reporting results. Results are reported in two ways. The panel named Data Mining Preliminary Results displays the results of the chosen algorithm in their “raw” form. The panel named Filtered Results displays the results in their interpreted form using domain derived heuristics. The overall data mining interface is illustrated in Figure 3 (a) and illustrated the hierarchy of stacked panels for the different data mining scenarios.

In this scenario, an Air Handling Unit (AHU) is selected as the building component that a user wishes to apply Data Mining to. The following sequence of actions is then followed:

• The user navigates the building in a real-time and online 3D virtual environment as shown in Figure 3 (a);

• Once the user selects a building asset type such as the Air Handling Unit the object property window pops out describing general information of the selected object as shown in Figure 3 (a).;

• Then, the Interface is invoked and the main window pops up to allow selection of algorithms as illustrated in Figure 4 (a);

• User explores a variety of data mining algorithms and chooses the desired algorithm and runs it as shown in Figure 4 (b);

• The Maintenance Agent running the algorithm is invoked and results are reported first in the Data Mining Preliminary Results panel as illustrated in Figure 4 (c);

• User selects Filtered Results in order to access post-processed knowledge and an example of filtered knowledge is shown in Figure 4 (d).

Data mining techniques assisted in identifying critical cost issues. For instance, discovering that corrective maintenance accounts for approximately 55% of all work orders implies a high level of unplanned maintenance that contributes to increasing the operational cost. The maintenance services required for the air conditioning system were related to thermal sensation complaints (too_hot 32%, too_cold 28%, not working 7.5%; total 67.5%). Hence, applying data mining techniques assists facility and building managers to identify the crucial maintenance issues and directs the improvement of strategic planning to add value to the life cycle of buildings.

Other benefits include constructing predictive plans based on correlations obtained from applying data mining techniques on the maintenance data sets of buildings. For instance, considering the role of potential correlations between seasons and malfunction rates in guiding the allocation of maintenance resources. Also, investigating any abnormal phenomenon discovered from the maintenance data set such as “all outstanding works took place in December”. An investigation is required to study the relationship between the cause of increasing the outstanding maintenance jobs taking place in December the Christmas holiday or any the other causes. Appropriately addressing this problem will lead to better activities to improve the maintenance management of existing facilities and will guide the design of future facilities (Reffat et al, 2004 a and b).

Conclusion

The development of data mining agents of facilities and building maintenance data in a 3D virtual environment provides a new approach for improving the maintenance and management of building facilities and guiding future design decisions. Virtual environments of building models offer the opportunity for the user to navigate through

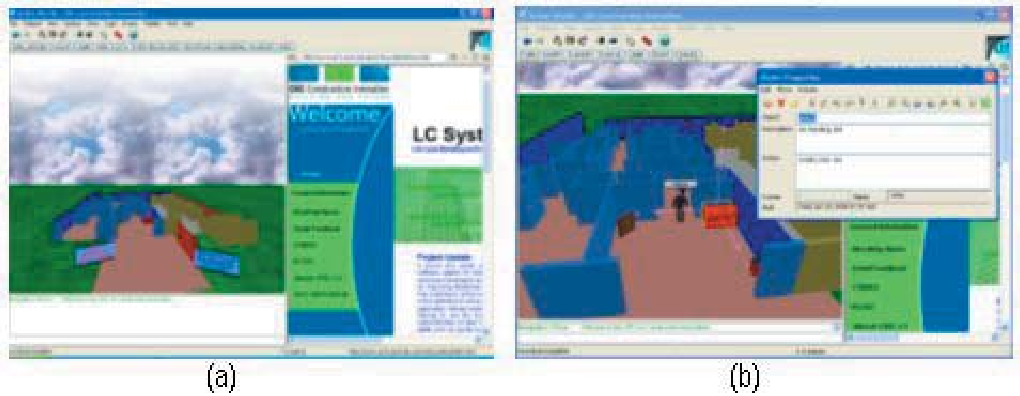

Figure 3. (a) The primary interface of software agents prototype system [AIMM] in an interactive network multi-user environment; and (b) The user selects a building asset type (the Air Handling Unit) and an object property window pops out describing general information of the selected object.

the model, to manipulate and to interact with its objects. The integration of facilities databases with interactive 3D virtual environments containing building models and data mining techniques provides a visual modelling tool for the simulation and projection of the financial and physical impact of maintenance, refurbishment and major replacement and extension of a building and its components over its live cycle.

The virtual mining environment has the potential to change the conventional approaches of applying data mining, and to provide a cutting edge technology to transform the way decision support for building maintenance is carried out presently and in the future. The virtual mining environment facilitates real-time assistance for decision making and provides an interactive platform for designers, building owners, facility managers and technicians to communicate and interact collaboratively and virtually within a 3D real time and multi user virtual environment. The building model presented in the real-time multi user virtual environment (Active Worlds) is composed of sets of 3D building elements. Building elements include walls, doors,

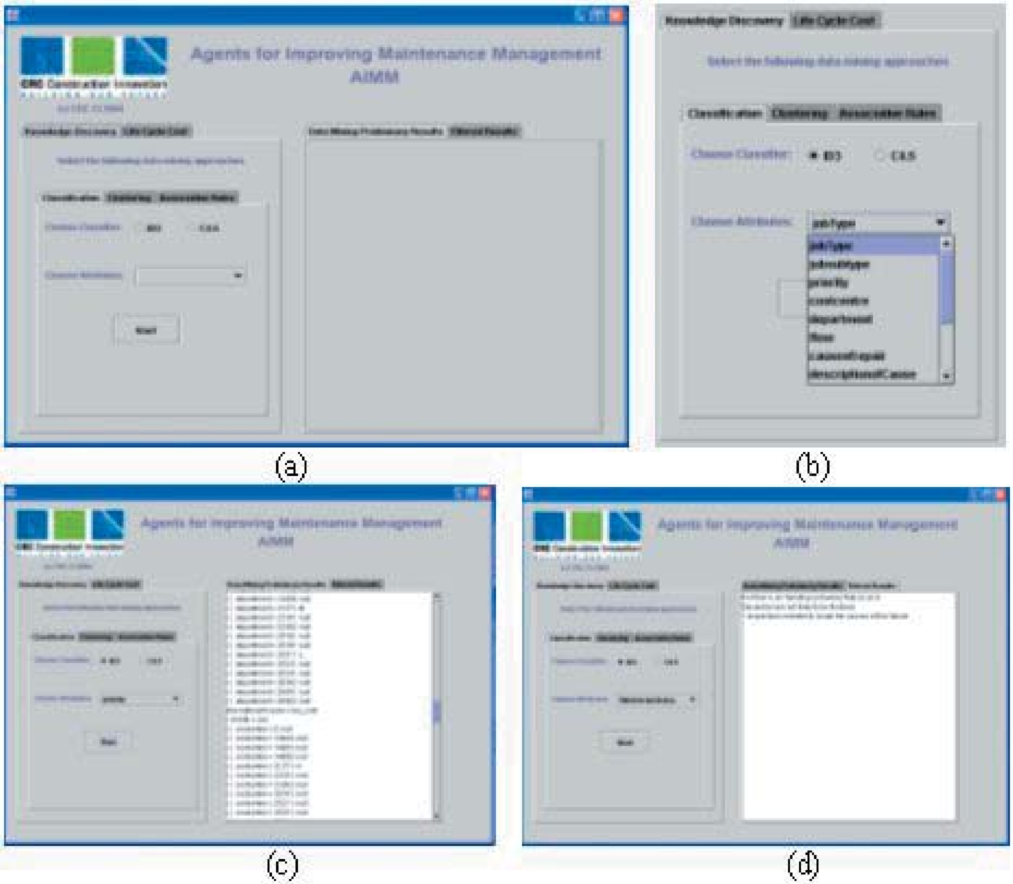

Figure 4. (a) The AIMM prototype system is instantiated once a building asset type has been selected; (b) Data mining techniques and different attributes for the user to choose from based on focus and interest; (c) Preliminary results of applying the ID3 with the "Priority" attribute on the maintenance data of Air Handling Unit; and (d) An example of the filtered knowledge presented to the user from the preliminary results of applying the ID3 with the "Work Order Status" attribute on the maintenance data of Air Handling Unit.

floors, windows, roof, and mechanical and electrical equipments. Each building element is linked to both a knowledge-base (that includes the maintenance records of that element), and to a data-mining agent triggered based on user's request to mine the knowledge-base and provide useful knowledge that help enhancing the decision making process to maintain and mange building facilities.

Data mining of building maintenance can help to discover: procedures that reduce future failures; repairs or maintenance operations that are being executed improperly; ways to improve repairs that reduces subsequent down time; undocumented methods being used by experienced personnel that result in reduced down time; advance notice of likely failures before failures occur. Such discoveries can be used to modify building maintenance and repair procedures thereby reducing downtime, increasing uptime, and significantly reducing the costs of maintenance and repair.

Furthermore, the knowledge-base of building elements is not static since all daily maintenance actions that took place are updated in the knowledge-base. Hence, the knowledge acquired by data-mining agents is active and dynamic. Therefore, the virtual mining environment facilitates providing a live, active and dynamic decision support on building maintenance to improve its maintenance management and the building life-cycle.

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