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A Case-based Reasoning System for Monitoring the Longevity of Dental Restorations

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Changes in dental restoration treatment patterns, combined with the introduction of new improved restorative materials and techniques, has greatly influenced the longevity of dental restorations. During the last decades there have been a great advantage in the restoration field. Since mid-1980's adhesive resin systems have been advocated for use in bonding amalgam to tooth structure and the advantages of bonded amalgams have been proved. The aim of this paper is to show how is evolving the field of the dental restoration and how composite restoration is gaining the battle to amalgam restoration with the help of a case-based reasoning system. This problem solving technique has been used to monitor the evolution of the dental restoration over the last decade using historical data and expert knowledge.

1 INTRODUCTION

Marked changes in the use of restorative materials have occurred during the past 20 years and aesthetic considerations are of growing importance for the restoration of posterior teeth. Alleged adverse health effects and environmental concerns associated with the release or mercury gave rise to controversial discussions about the use of amalgam as a contemporary restorative material. Moreover there is a growing concern about the use of metallic alternatives to amalgam restorations include glass ionomers, direct composite restorations, composite inlays and ceramic inlays. The amalgam is considered, by the scientific community as the restoration material less sensible to the to the odontologic technique. This material has also adequate mechanical properties and requires a relatively small clinical working time. The main drawback of the amalgam is its poor aesthetical results and the controversial toxicity related to problems due to its mercury based composition and potential dental fractures, secondary caries, and marginal filtrations (Burke *et al.*, 1999; Smales *et al.*, 1991).

Composite materials have evolve during the last decades and have solved some of their problems related for example to their mechanical properties, the sealing of the posterior pieces, etc. Nevertheless, there are still important problems related to this materials such as marginal degradations, restoration fractures, discoloration of borderlines, secondary caries, etc. These reasons are delaying the expansion of composite materials (Mjör, 1992; Mjör and Toffenetti, 1992; Wilson *et al.*, 1997).

The importance given to aesthetical factors by the population and the importance given to the mouth health care, together with the advances in composite materials that facilitate realistic designs and in new adhesive systems (Scheibenbogen-Fuchsbrunner *et al.*, 1999) have made that the composite restorations lead the conservative odontological treatments demanded by the population. Although amalgam restoration remains the most popular restorative material for posterior restoration the use of resin-based composites and adhesive systems are becoming more and more frequently, and are in the way to overtake the number of amalgam restorations carried out in the posterior part.

The evaluation of the progression of dental restorations can be carried out with longitudinal and transversal techniques (Mjör and Toffenetti, 1992; Mjör, 1997). The first ones are more specific and selective with respect to the used variable. The transversal studies or clinic Cross sequential require less definition and may be used to carry out forecast in the short time. We believe that a case-based reasoning (CBR) system can be used to monitor and predict the evolution of the restorations with a higher degree of success that any other statistical technique.

The study of this technological change should be used to identify the rate of change and the evolution of both complementary restoration techniques: composite and amalgam. A tool has been developed to monitor and predict the longevity of restorations. This tool is based on a Case-based reasoning System and has been tested in Vera dental surgery (Madrid). The CBR based tool stores records of all patients, including information related to dental restorations. This information is then used to identify the longevity of the restoration and the number and type of restorations that have to be carried out in a weekly base.

First the case-based reasoning system model is going to be introduced. Then the case-based reasoning system developed for predicting the evolution of restorations will be presented and finally the results obtained with it will be outlined.

2 CASE-BASED REASONING SYSTEMS

Although knowledge-based systems (KBS) represent one of the commercial successes of the outcome of artificial intelligence research, developers of these systems have encountered several problems (Watson and Marir, 1994). Knowledge elicitation, a necessary process in the development of rule-based systems, can be problematic. The implementation of a KBS can also be complex, and, once implemented, may also be difficult to maintain. With the aim of overcoming these problems Schank (1982) proposed a revolutionary approach, case-based reasoning, which is in fact a model of human reasoning (Joh, 1997). The idea underlying CBR is that people frequently rely on previous problem-solving experiences when solving new problems. This assertion may be verified in many day to day problem solving situations by simple observation or by psychological experimentation (Klein and Whitaker, 1988). Since the ideas underlying case-based reasoning were first proposed, CBR systems have been found to be successful in a wide range of application areas (Kolodner, 1993).

A case-based reasoning system solves new problems by adapting solutions that were used to solve previous problems (Riesbeck and Schank, 1989). The case base holds a number of cases, each of which represents a problem together with its corresponding solution. Once a new problem arises, a possible solution to it is obtained by retrieving similar cases from the case base and studying their recorded solutions. A CBR system is dynamic in the sense that, in operation, cases representing new problems together with their solutions are added to the case base, redundant cases are eliminated and others are created by combining existing cases.

A CBR system analyses a new problem situation, and by means of indexing algorithms, retrieves previously stored cases, together with their solution, by matching them against the new problem situation, then adapts them to provide a solution to the new problem by reusing knowledge stored in the form of cases in the case base. All of these actions are self-contained and may be represented by a cyclic sequence of processes, in which human interaction may possibly be needed. Case-base reasoning can be used by itself or as part of another intelligent or conventional computing system. Furthermore, case-based reasoning can be a particularly appropriate problem solving strategy when the knowledge required to formulate a rule-based model of the domain is difficult to obtain, or when the number or complexity of rules relating to the problem domain is too great for conventional knowledge acquisition methods.

A typical CBR system is composed of four sequential steps which are called into action each time that a new problem is to be solved (Kolodner, 1993; Aamodt and Plaza 1994; Watson, 1997). Figure 1 outlines the basic CBR cycle.

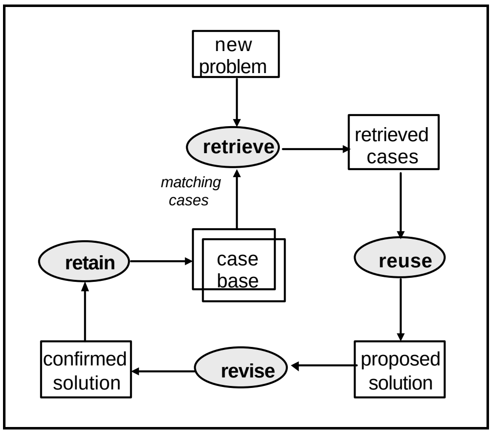

Figure 1. CBR Cycle

This cyclic process of CBR involves four major steps, represented by the ellipses in Figure 1:

- Retrieve the most relevant case(s),
- Reuse the case(s) to attempt to solve the problem,
- Revise the proposed solution if necessary, and
- Retain the new solution as a part of a new case.

The purpose of the retrieval step is to search the case base and to select from it one or more previous cases that most closely match the new problem situation, together with their solutions.

The selected cases are reused to generate a solution appropriate to the current problem situation. This solution is revised if necessary and finally the new case (i.e. the problem description together with the obtained solution) is stored in the case base. Cases may be deleted if they are found to produce inaccurate solutions, they may be merged together to create more generalised solutions, and they may be modified, over time, through the experience gained in producing improved solutions. If an attempt to solve a problem fails and it is possible to identify the reason for the failure, then this information should also be remembered in order to avoid the same mistake in the future. This corresponds to a common learning strategy employed in human problem solving. Rather than creating general relationships between problem descriptors and conclusions, as is the case with rule-based reasoning, or relying on general knowledge of the problem domain, CBR systems are able to utilise the specific knowledge of previously experienced concrete problem situations. A CBR system provides an incremental learning process because each time that a problem is solved a new experience is retained, thus making it available for future reuse.

In the CBR cycle there is normally some human interaction. Whilst case retrieval and reuse may be automated, case revision and retention are often undertaken by human experts. This is a current weakness of CBR systems and one of their major challenges. In this paper a method of automating the process of case adaptation (revision) is presented for the solution of problems in which the cases are characterised predominantly by numerical information.

The Instance-based reasoning systems are highly syntactic CBR-approaches (Aamodt and Plaza, 1994). In cases where there is a lack of guidance from general background knowledge, a relatively large number of instances are needed in order to obtain a concept definition or solution. The representation of the instances are usually simple (e.g. feature vectors), since a major focus is to study automated learning without user intervention (Aha, 1991).

2.1 CBR Systems for Modelling

Several researchers (Navinchandra *et al.*, 1991; Lendaris and Fraser, 1994) have used k-nearest-neighbour algorithms for time series prediction and modelling. Although a k-nearest-neighbour algorithm does not, in itself, constitute a CBR system, it may be regarded as a very basic and limited form of CBR operation in numerical domains. Navinchandra *et al.* (1991) uses a relatively complex hybrid CBR system. In contrast, Lendaris and Fraser (1994) model a data set just by searching in a given sequence of data values for segments that closely match the pattern of the last n measurements and then by supposing that similar antecedent segments are likely to be followed by similar consequent segments.

In most of the cases the CBR systems used in forecasting problems have a flat memories with simple data representation structures. In the majority of the systems surveyed case revision (if carried out at all) is performed by human expert, and in all the cases the CBR systems are provided of a small case-base. A survey of such forecasting CBR systems can be found in Corchado and Fyfe, (1999).

3 APPLYING CASE BASED REASONING SYSTEM TO DENTAL RESTORATION

The aim of the CBR system here presented is to identify the longevity of the restorations and the number and type of restorations that have to be carried out, in a surgery, in a weekly bases. The case hold information about the restorations carried out in the pass. A case is created with each new restoration. It includes information about the type of restoration, the tooth (dental piece) affected, date of restoration and date of the restoration modification, number of restoration in that particular tooth, total number of restorations and details of the patient such as age, sex, name, etc.

The reasoning cycle of the CBR systems covers four stages as mentioned before. During the retrieval, a k-nearest neighbour metric is used to select the cases that are more similar to the problem case. The metric identify cases that include restorations carried out in patients with the same characteristics that the problem one, cases associated to the patient under treatment and with the same type of restoration. Relaxation techniques have been used as in (Watson and Gadingen, 1999).

The adaptation is carried out using a radial basis function artificial neural network (ANN) as in Corchado and Lees (2001).The ANN creates a model with the retrieved cases that can be used to identify the longevity of a particular restoration.

Year	86	87	88	89	90	91	92	93	94	95	96	97	98	99	00
no. patient/day	20	20	19	20	21	19	20	21	17	18	18	21	22	23	21
no. restor. / day	7	6	6	7	7	7	6	7	5	8	9	10	10	11	9
no. resin restor. / day	2	3	3	4	3	3	3	4	3	5	5	6	7	8	7
no. amal. Restor. / day	5	3	3	3	4	4	3	3	2	3	4	4	3	3	2

Table 1: Number of restorations per day.

The revision process is carried out using Belief Revision techniques (Pavón *et al.*, 2001). A rule-based system is used during this phase, which is updated automatically using a Belief Revision technique that uses Epistemic Entrenchment, as constructive model. After the forecast is done, it is stored and compared with the real output. Once a new case is created, it is stored in temporal case-base.

4 RESULTS AND CONCLUSIONS

The CBR tool constructed in the framework of this investigation, can be use to identify the number of restorations that will be carried out each week, in advance, and to determine the expected longevity of each restoration. Table 1 shows the number of restorations carried out in "Vera dental surgery" over the last few years.

Looking at this table can be seen how the number of resin based restorations is increasing with time in detriment of the number of amalgam based restoration. The CBR system has helped us to determine the longevity of the resin and amalgam restorations carried out over the last 8 years with an average error of 6 months in the case in the amalgam restorations, and 3 month in the case of resin restoration. This information can be also used to identify the number of restorations that will be carried out in a month. In this case the average error for the amalgam restoration is of 0.2 restorations/month and in the case of resin restoration is of 0.4 restorations/month.

This paper is a first step in the development of a robust system for the monitoring and prediction of the evolution of restorations. The development of this system requires to analyse and to include more variables and historical data. A distributed database is under construction to store information from a significant number of dental surgeries. After centralising all of this information, we will have enough information to construct a more solid and efficient system based on the initial successful results obtained and presented in this paper.

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