We present a Web-based knowledge management and decision support system for Type I Diabetes patients’ care. The tool exploits the integration of two methodologies, Case Based Reasoning and Rule Based Reasoning, and supports physicians in the definition of therapeutic strategies. Such a work is being integrated in the EU funded T-IDDM project architecture. In this paper we report a first evaluation obtained on simulated patients.

INTRODUCTION

The introduction of hospital information systems into the clinical practice has led to the memorization of large amounts of data, extracted from day by day experience, thus making available a new type of knowledge, which can be exploited together with the general domain one. A problem of management and maintenance of such information has arisen. Knowledge Management (KM) can be defined as a discipline for realizing an integrated approach to managing and sharing the overall hospital information. Such information may be stored in databases and in documents, or may be represented by the unarticulated experience of individual workers. It is possible to rely on different instruments for the KM task. When dealing with chronic diseases management, one of the most effective is Case Based Reasoning (CBR). In such a context, the data collected from patients’ follow up (stored in the case library) embody an important knowledge source, to be integrated with the available declarative knowledge (that can be represented by other formalisms, e.g. rules). The case library permits the maintenance of a specific patient’s history, so that, even in presence of changes in the physicians’ staff, the quality of care will not decrease due to a lack of information. Moreover, it stores the “operative” knowledge of experts, which can be kept and reused in the institution even when they move or retire. To take advantage from the exploitation of both contextual and general knowledge, the recent advances in Information Technology have led to the design of a new generation of KM and decision support systems, that often rely on the cooperation of different reasoning paradigms. Particular attention has received the combination of CBR and Rule based Reasoning (RBR), being rules the most successful knowledge representation formalism for intelligent systems, and being CBR well suited for integration with formalisms grounded on general, declarative knowledge. While in the majority of the tools described in literature, CBR and RBR are used in a quite exclusive way, our approach aims at leading to a very tight integration, taking place within a general problem solving cycle. Two are the main limitations arising from the use of the two paradigms in a not cooperative way. On the first side, classical RBR systems don’t have the capability of specializing the declarative knowledge embedded in the rules, by resorting to the contextual knowledge (e.g. the patient at hand’s characteristics). The risk one may incur in is the definition of a very large set of rules, meant to deal with as much peculiar situations as possible (the so-called qualification problem). On the other hand, CBR just relies on the contextual knowledge stored in the case library. A misleading indication on how to solve the current problem may emerge when the number of cases is too small, or when the retrieved information is polarized on too specific examples. The capability of filling such a competence gap is crucial in medical applications, since final decisions should be always based on established knowledge. Our approach aims at overcoming these limitations, by building a KM and decision support tool able to specialize declarative knowledge with the information coming from direct experience, and to dynamically adapt rules on the basis of the patient’s features. In addition, our system generalizes the contextual knowledge by abstracting from cases common indications, and by exploiting rules to learn suitable solutions, improving the competence of the case-based component when a particular patient condition is not sufficiently covered by cases. A natural way of performing the integration among different reasoning paradigms, and with the Hospital Information System, is to resort to a Web-based environment for data management and results presentation. In the following sections, we describe the design of a CBR and RBR cooperation tool for Type I Diabetes (IDDM) patients management, and its implementation within the Web-based, distributed architecture developed in the context of the EU funded T-IDDM project, together with a first evaluation obtained through the use of an IDDM patient simulator.

IDDM PATIENTS MANAGEMENT

Diabetes Mellitus is a major chronic disease in the industrialized countries. In particular, IDDM patients need insulin injections to regulate blood glucose metabolism, in order to prevent acute episodes, such as ketoacidosis and coma, as well as later life invalidating complications. Intensive Insulin Therapy (IIT), consisting in 3 to 4 injections
every day, or in the use of subcutaneous insulin pumps, may reduce the outlined risks, but, on the other hand, will increase the IDDM therapy costs. In fact, the management of patients undergoing IIT is a complex task, as they need to be visited every 2-4 months, in order to assess their metabolic condition, and, if needed, to revise the therapy. During periodical visits, physicians have to analyze a large amount of data, coming from home monitoring (blood glucose measurements, taken before every injection, insulin doses and diet information), from physical examination (e.g. weight), and from lab analysis (e.g. HbA1c). In order to revise the therapeutic protocol on the basis of the collected information, they may rely both on structured knowledge (i.e. on insulin pharmacodynamics), and on previous experience (i.e. the observation that a certain protocol has been applied on that patient or to patients with similar characteristics in the past, with a particular outcome). Integration among RBR and CBR seems therefore a natural solution when building a decision support system to be applied in this context. While RBR has been largely exploited, no examples of CBR approaches in IDDM management can be found in the literature, although, being IDDM a chronic disease, the use of CBR would provide clear advantages in management and maintenance of contextual knowledge. The tool we have developed is meant to manage the domain knowledge and the contextual one, and to exploit both, resorting to an integration of the RBR and CBR. With the use of this tool, we also expect to have important drawbacks for what concerns IDDM management costs: keeping track of the overall patient’s history will help physicians in continuously controlling her/his possible metabolic alterations, and in reaching stabilization in a shorter time.

SYSTEM DESIGN

The RBR tool
The declarative knowledge collected from domain experts’ opinion is embedded into a taxonomy of production rule classes, fired through a forward chaining mechanism. Each rule class performs an action:

- Data analysis and problem identification: after having computed some indicators of the patient’s metabolic condition, the system identifies hypoglycemia or hyperglycemia problems.
- Suggestion generation: for each detected problem, a set of alternative suggestions, dealing with insulin therapy, diet or physical exercise, is generated.
- Suggestion selection: the most suitable and effective suggestions are selected and applied to the current therapeutic protocol.
- Protocol revision: the adjusted protocol, together with other library protocols suitable for the situation at hand, is listed to physician for her/his final judgment.

Additional details on the RBR tool can be found elsewhere. Some first encouraging results on the RBR tool performances have emerged from a series of tests made on simulated patients, and from the real patients’ outcome evaluated at the end of the T-IDDM verification phase.

The CBR tool
In the CBR component of our application, a case is defined by a set of feature-value pairs, by a solution and by an outcome. The case features are the data collected during a periodical visit. The solution is the therapeutic protocol assigned by the physician after the features examination, and the outcome of such therapy is given by the number of hypoglycemic episodes and by the value of HbA1c collected at the following visit (i.e. the following case). The case library structure strongly influences the case search; to make retrieval more flexible we have structured it by resorting to a taxonomy of mutually exclusive prototypical classes, that express typical problems that may occur to patients in the age of infancy and puberty. A more complete taxonomy will be defined before testing the system in adult patients’ clinics. Case retrieval is then implemented as a two step procedure: a classification step, that limits the case search to a subset of the classes into which the library is divided, and a proper retrieval step, meant to effectively identify the “closest” cases. Classification relies on a Naive Bayes strategy, a method that assumes conditional independence among the features given a certain class, but that is known to be robust in a variety of situations, even in the presence of conditional dependencies. Prior probabilities have been derived through the collaboration with the diabetologists of the Pediatric Department of Policlinico S. Matteo in Pavia, while posterior probabilities were learnt from the available case base (145 cases from the histories of 29 pediatric patients) by using a standard Bayesian updating technique. Retrieval may be performed just on the most probable class identified by the classification step, or on a subset of the most probable classes. In both situations the system relies on a Nearest-Neighbor (NN) technique and classical metrics, able to treat numeric and symbolic variables, and to cope with the problem of missing data, are applied to calculate distances. When dealing with a large case-base, our application implements a non exhaustive search procedure that exploits an anytime algorithm called Pivoting-Based Retrieval (PBR), whose efficacy has been proved on a 10000 cases library.
Integration between CBR and RBR

CBR results are integrated in the RBR framework by means of a rule refinement process involving the change of suitable rule parameters on the basis of information obtained from the case library (i.e. classification and retrieval). In particular, the rule classes dealing with problem identification and suggestion generation are affected by the integration procedure. Their behavior is refined, in order to be properly tailored on the specific patient’s needs.

Figure 1 summarizes the overall procedure, which is performed in the following way:

- The Bayesian classifier is invoked on the patient’s visit data.
- If the physician chooses to rely on the classification results, the most probable class information is used to specialize the problem identification rules parameters.
- The physician may want to complete the classification information with retrieval results. A test on the retrieved cases is performed; only cases whose protocol has the same injection number of the input case will be considered. If no such a case is retrieved, RBR is applied without CBR integration.
- Among the remaining cases, the tool just exploits the ones with a positive outcome (i.e. cases for which the applied protocol has resulted in a low number of hypoglycemic events and in a HbA1c decreasing trend). On them, it computes some descriptive statistics, to set parameters such as the number of insulin injections, the variation in the daily insulin requirement and the variation of a single insulin dose, thus specializing the suggestion rules class.
- The result of the previous rule specialization is a list of refined suggestions, which can be used to complete the RBR cycle, for providing the physician with a final outcome.

On the other hand, CBR can take advantage from the results of RBR as well. When no suitable case is retrieved by the CBR component (either because no positive outcome is found or because the retrieved therapeutic protocols are significantly different from the current one), we can infer that the input case belongs to a competence gap region. In such a situation, our tool performs RBR without integration, in order to avoid wrong specialization due to misleading cases. As soon as the outcome of the proposed protocol is available (normally at the next periodical visit), a new case is learnt, and stored in the memory, to fill the competence gap.

IMPLEMENTATION DETAILS

The CBR and the RBR tools have been developed in the context of the EU funded T-IDDM project. The T-IDDM service is provided by the communication of two main modules: a Patient Unit (PU), residing at the patient’s house, and meant to help the activities of data collection and self monitoring, and a Medical Unit (MU). The latter is a collection of tools for data visualization, data analysis, knowledge management and decision support, accessible by physicians through a common Web browser. The communication between the two main units, and the interaction among the tools of the Medical Unit relies on lisweb. Lisweb is an extended, special-purpose Web server written in Common Lisp, that makes it possible to create “intelligent” and “secure” applications while remaining in the context of Web-
based systems, to which physicians are nowadays familiar.

RESULTS

Up to now, we have made some preliminary tests of our system functionality by comparing the performances of RBR with the ones of the CBR-RBR integrated approach in stabilizing the metabolic control of a simulated patient. More in detail, the patient’s main features have been taken from the description of a real pediatric patient of our case base, while her blood glucose measurements have been generated by a simulator\textsuperscript{19}. We have performed an iterative procedure, that consisted in simulating 7 days of measurement (3 measures per day plus some post-prandial data; to introduce intra-patient variability, the data were derived adding a 10% noise on the simulation results), and then in revising the therapeutic protocol. The revised protocols were acquired by the simulator and used to obtain the data for the following monitoring period. Such procedure ended when the simulated patient metabolic condition was stabilized.

The test patient was a girl of 19, with a weight of 40 kg and a height of 160 cm, a HbA1c value of 5.1% and an insulin requirement of 0.6 units/kg/day.

The input case was classified by the CBR system as an example of anorexia, and this information was used to specialize the problem identification rules. 20 cases were retrieved through a NN technique, and from them a significant result about NPH insulin doses variation was obtained: while the default variation in each dose is of 1 unit in the non-specialized suggestion generation rules, in the retrieved cases the average variation was of 4 doses. This indication was used to further contextualize the RBR behavior. Figure 2 shows the outcome of the RBR system, while figure 3 shows the outcome of the integration approach.

Being the RBR system more conservative, it took 4 weeks (i.e. 4 adjustments) to stabilize the simulated patient. On the other hand, the integrated approach, made more aggressive by rules specialization, just took 1 adjustment to produce the same result.

CONCLUSIONS

As the results obtained on simulated patients suggest, we believe that the approach of CBR and RBR integration described in this paper will provide physicians with a therapy suggestion properly tailored on the patient’s peculiar needs. We expect to obtain some more significant feedback directly from patients and physicians taking part to the T-IDDM demonstration phase, that will involve people from three different diabetological centers: a pediatric one in Pavia, and two adult patients clinics in Barcelona and in Helsinki. We plan to test the effectiveness of the system, and of the overall T-IDDM service, not only by proving the metabolic enhancement of patients, but also assessing a reduction in the time needed to evaluate patient’s data and to revise therapy during periodical visits. In fact, before the patient undergoes a visit, the physicians will have already received her/his home monitoring data through the PU-MU communication. Therefore they will have already analyzed the overall metabolic condition, and obtained some therapy suggestions from the CBR-RBR tool. These indications will just have to be tuned on the additional parameters collected during the visit itself.
In addition to these possible advantages in therapy planning, we forecast that our tool will permit an easier knowledge management, and a better cooperation between contextual data and declarative information. Finally, the accessibility of the system via Web will extend the system’s usability. The service of contextual knowledge management and maintenance will provide the dissemination of experts’ knowledge towards other physicians and towards other hospital centers, and could be adopted as an educational tool for non-specialized physicians or even for patients. Moreover, the decision support service could be remotely accessed by different diabetological centers or by GPs, providing a teleconsultation aid. Considering all these possible applications, we also plan to work on possible implementations of the described tool in the context of different chronic disease management.

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