A multi-modal reasoning methodology for managing IDDM patients

Stefania Montani a,*, Riccardo Bellazzi a, Luigi Portinale b, Mario Stefanelli a

a Dipartimento di Informatica e Sistemistica, Università di Pavia, Via Ferrata 1, I-27100 Pavia, Italy
b Dipartimento di Scienze e Tecnologie Avanzate, Università del Piemonte Orientale, Alessandria, Italy

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Abstract

We present a knowledge management and decision support methodology for insulin dependent diabetes mellitus (IDDM) patients care. Such methodology exploits the integration of case based reasoning (CBR) and rule based reasoning (RBR), with the aim of helping physicians during therapy planning, by overcoming the intrinsic limitations shown by the independent application of the two reasoning paradigms. RBR provides suggestions on the basis of a situation detection mechanism that relies on formalized prior knowledge; CBR is used to specialize and dynamically adapt the rules on the basis of the patient’s characteristics and of the accumulated experience. When the case library is not representative of the overall population, only RBR is applied to define a therapy for the input situation, which can then be retained, enriching the case library competence. The paper reports the first evaluation results, obtained both on simulated examples and on real patients. This work was developed within the EU funded telematic management of insulin dependent diabetes mellitus (T-IDDM) project, and is fully integrated in its web-based architecture. © 2000 Elsevier Science Ireland Ltd. All rights reserved.

Keywords: Multi-modal reasoning; Case based reasoning; Knowledge management; Therapy planning; Diabetes mellitus

1. Introduction

Managing the overall amount of information stored into a hospital information system (HIS), collected during the day by day clinical practice, is a complex task. Knowledge management (KM) is a discipline that aims at coping with the even larger problem of maintaining, together with the data stored in the database, also the information contained in documents, or represented by the unarticulated experience of individual workers. In the context of chronic disease management, KM can be implemented by resorting to the case-based reasoning (CBR) methodology. CBR [1] is a problem-solving paradigm that uses the ‘operative’ knowledge of previously experienced situations, called cases.
Past cases similar to the current one are retrieved and shown to the user. Case based retrieval, by enabling physicians in performing an intelligent consultation of the available data-bases, keeps track of the ‘problem/solution’ patterns that occurred in the past. The highest quality of care is always the main objective of KM in the disease management context; the case library, keeping track of a specific patient’s history, guarantees the maintenance of all the necessary information in the presence of changes in the physician’s staff; at the same time, even when a physician moves or retires, her expertise is constantly made available to the colleagues. In the classical CBR cycle, the past successful solutions are also adapted to the present problem and reused; however, such adaptation step may lead to inaccurate suggestions, when the patients population is poorly represented in the case library. The space of cases may in fact present some regions not covered by a sufficient number of cases (competence gaps), the case library being itself too small, or being the information polarized on too specific examples. The capability of filling such competence gaps is crucial in medical applications, since final decisions should be always based on established knowledge. To overcome this potential problem, a useful choice is to integrate CBR with a rule-based reasoning (RBR) system, rules being the most successful knowledge representation formalism for intelligent systems. In this way it is possible to take advantage not only from the operative knowledge of the health care institution, but also from the formalized knowledge of the sector. In the majority of the tools described in literature, CBR and RBR are used in quite an exclusive way. In some applications, a rule-based system that deals with knowledge on standard situations is applied first. When it is not able to provide the user with a reliable solution, the CBR technique is used, by retrieving similar cases from a database of peculiar and non-standard situations [2]. A different approach suggests using rules as an ‘abstract’ description of a situation, while cases represent a further ‘specialization’. Cases assist RBR by instantiating rules, while rules assist CBR by permitting the extraction of more general concepts from concrete examples [3]. It is possible to decide ‘a priori’ which method should be applied first, or to select the most convenient one in a dynamic way, depending on the situation at hand [3,4]. In particular, the rule base and the case library can be searched in parallel for applicable entities. Then the best entity (i.e. rule or case) to reuse (and, therefore, the reasoning paradigm to apply) can be selected on the basis of its suitability for solving the current problem [4]. Finally, RBR can support CBR after the retrieval phase, during the adaptation task; if the library does not contain suitable examples of adaptations of past cases to situations similar to the current one, the system relies on some general adaptation rules [5]. In this paper, we present an approach that aims at leading to a very tight integration, taking place within the general problem solving cycle, in order to overcome the limitations of the two reasoning paradigms. Somehow like [3], we aim at exploiting CBR to specialize the rules on the basis of the patient’s characteristics, without highly increasing their number, therefore coping with the so-called qualification problem [6], a well-known RBR weakness; moreover we would like some rules (or part of them) to be dynamically adapted on the basis of the past available experience. On the other hand, CBR just relies on the contextual knowledge stored in the case library that, as noted earlier, may be affected by the presence of competence gaps. Our methodology is able to generalize the contextual knowledge embedded in cases, and to exploit rules to learn
suitable solutions for those situations not well represented by earlier experience. Following such approach, we have defined a multi-modal decision support tool for the management of diabetic patients, fully integrated within the EU T-IDDM project web-based environment [7,8].

2. Diabetes management

Diabetes mellitus is a major chronic disease, affecting up to 3% of the population in the industrialized countries. In particular, Insulin Dependent Diabetes Mellitus (IDDM) patients need exogenous insulin injections to regulate blood glucose metabolism, in order to prevent ketoacidosis and coma, and to reduce the risk of later life invalidating complications. It has been proved [9] that Intensive Insulin Therapy (IIT), consisting of three to four injections every day, or in the use of subcutaneous insulin pumps, is the most effective way to stabilize blood glucose, and therefore, to reduce or delay IDDM complications; the increase in therapy planning complexity and in costs is the obvious drawback. IDDM management normally consists of visiting patients every 2–4 months; during these control visits the data coming from home monitoring are analyzed, in order to assess the metabolic control achieved by the patients. Laboratory results and historical and/or anamnestic data are verified as well, in order to finally revise the patient’s therapeutic protocol. During the overall process, the physician may propose a solution to the patient’s problems relying on formalized knowledge (e.g. the pharmacodynamics of insulin), as well as, on operative knowledge (i.e. the specific patient behavior, or the previous experience collected at the diabetological center). Our methodology, enabling the exploitation of both the knowledge sources, therefore, seems a valuable way of proving decision support in this context.

3. Multi-modal reasoning for diabetes management

3.1. The CBR system

In our implementation of the CBR methodology, a case consists in a periodical visit, and is represented by a set of features (i.e. the data collected during a periodical visit), by a solution (i.e. the therapeutic protocol assigned after the features examination), and by an outcome (given by the number of hypoglycemic episodes and by the value of HbA1c collected at the following visit). By cooperating with the pediatricians of Policlinico S. Matteo hospital in Pavia, we were able to build a case library made by 145 cases, extracted from the histories of 29 young patients. The case library organization strongly influences the case search performances; to make retrieval more flexible we have structured it as a tree, mirroring a taxonomy of mutually exclusive prototypical classes, that express typical problems that may occur to patients in the age of infancy and puberty (Fig. 1). Each case belongs to one leaf of the tree.

Such taxonomical cases’ organization has allowed us to perform retrieval as a two-step procedure. The input case is first classified as belonging to a leaf, or class; the search is then limited to a region of the case library, made by the most probable class for the input case (intra-class retrieval), or by a set of the most probable classes (inter-class retrieval). 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 [10,11], even in the pres-
Fig. 1. Taxonomy of prototypical situations that may occur to pediatric IDDM patients.

The method classifies a case as belonging to the class that maximizes $P(c_i| f = \hat{f})$. The conditional probabilities $p(f_j = \hat{f}_j| c_i)$ are obtained through the Bayesian update formula for discrete distributions [12,13]; in particular, we use a re-parameterized version of the update formula known as m-estimate of probability [14], that modifies the prior knowledge with the information coming from the cases of the case memory as follows:

$$p(f_j = \hat{f}_j| c_i) = \frac{m \hat{p}_j + \hat{N}_j}{m + D_i}$$

where $\hat{N}_j$ is the number of cases in the case memory of class $i$ whose feature $f_j$ assumes the value $\hat{f}_j$, while $D_i$ is the total number of cases in class $i$. The medical knowledge is
synthesized by the prior probability distribution \( (p_{ij}) \), whose reliability is expressed by the implicit number of samples \( m \). In other words, the larger the \( m \), the larger is the confidence of the expert on the prior.

In our application, the prior probability value \( (p_{ij}) \) was derived from expert’s opinion through a technique described in [15].

The second step of the retrieval procedure consists in actually finding the most similar cases in the reduced search space, exploiting a Nearest-Neighbor (NN) technique. The user is allowed to choose whether to retrieve cases belonging only to the most probable class identified by the classifier (intra-class retrieval), or to a set of possible classes (inter-class retrieval). In the first hypothesis, distance is computed using the heterogeneous euclidean-overlap metric (HEOM) formula; in the second hypothesis, using the heterogeneous value difference metric (HVDM) formula. Both metrics are able to treat numeric and symbolic variables, and to cope with the problem of missing data [16]. When dealing with a large case-base, our application implements a non-exhaustive search procedure that exploits an anytime algorithm called pivot-based retrieval (PBR) [17], that significantly speeds up the retrieval time [18].

Fig. 2 summarizes the steps of the case based retrieval procedure; additional details may be found in [18]. Retrieval results are exploited to specialize the RBR behavior.

3.2. The RBR system

The activity of the RBR system has been implemented through the episodic skeletal planning method (ESPM) [19]. The ESPM assumes the existence of a skeletal plan, (in the IDDM context, a therapeutic protocol), made by a set of constituent subplans (i.e. the insulin plan, the diet plan, the exercise plan). In particular, the RBR system acts on the insulin plan structure. The goal of our implementation of ESPM is to provide the patients with a protocol able to solve their metabolic problems, by revising and adjusting the one they were following since the latest revision. The method is said to be episodic as it is invoked several times: in fact, therapy is revised at least at every patient’s visit, in routine clinical practice, and also at additional time instants through teleconsultation, when exploiting the T-IDDM service. Every time, the RBR system analyzes a patient’s data and the therapeutic actions that are still in progress, and suggests an appropriate therapy by refining the insulin plan. In our system, the ESPM is structured in four reasoning tasks, each one performed by a rule class in a taxonomy of production rules, fired through a forward chaining mechanism:

- **Problem identification**: the data are temporally contextualized according to a qualitative time scale obtained by subdividing the day into seven non-overlapping time slices, that are centered on the injection and/or meal times. After having computed some indicators of the patient’s metabolic condition, and in particular the blood glucose level (BGL) modal day, an indicator able to summarize the average response of the patient to a certain therapy [20], the system identifies hypoglycemia or hyperglycemia problems. In particular, when the frequency of a certain blood glucose qualitative level is higher than a given threshold, and when the number of missing data is sufficiently small to rely on such information, a problem is identified. For example, the following rule detects a hypoglycemia problem in a generic time slice \( Y \) using the information contained in the relative modal day component \( X \). The probability of hypoglycemia in the \( Y \) time slice belongs to an interval whose lower and upper bound are called minimum
probability and maximum probability, respectively [21]; the difference between them is proportional to the number of missing data and is denoted as the ignorance in the monitoring period.

IF X IS A BGL-MODAL-DAY-COMPONENT
AND THE TIME-SLICE OF X IS Y
AND THE BGL-LEVEL OF X IS LOW
AND THE MINIMUM-PROBABILITY OF X \geq \alpha
AND THE IGNORANCE OF X \geq \beta
THEN GENERATE-PROBLEM HYPOGLYCEMIA AT Y
where \alpha and \beta are two parameters that can be instantiated at run-time. Their default values, to be applied when no particular information about the case at hand is available, are equal to 0.3 and 0.8, respectively.

- **Suggestion generation**: for each detected problem, a set of alternative suggestions is generated.

- **Suggestion selection**: a subset of the generated suggestions is selected, in order to perform just the most effective action in every time slice.

- **Protocol revision**: by applying the selected suggestions to the current insulin plan, an adjusted therapeutic protocol is built; it is then listed together with other library protocols suitable for the situation at hand, and shown to the physician for her final judgment.

Additional details on the RBR tool can be found elsewhere [22]. Fig. 3 summarizes the overall reasoning process.

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 [23]; a limitation has been underlined as well: even if the RBR system generally mimics the expert’s behavior, it is too conservative in a variety of situations. The multi-modal reasoning methodology, by contextualizing the case, is meant to overcome this weakness.

### 3.3. RBR–CBR integration

The order in which the rules performing the four reasoning tasks described above have to be fired is determined by a set of metarules. The integration of CBR into this framework is achieved by defining additional metarules; the first metarule states that CBR is applied, at the beginning of the reasoning process, to the patient’s visit data, by performing the classification step. The classification results are used to specialize the problem detection rules, in the following way:

- setting a proper value of the threshold for the frequency of BGL qualitative abstractions;

- defining the maximum admissible number of missing data so that the information may be relied upon.

For example, when dealing with patients in the clinical remission phase, the rule described in section Section 3.2 becomes:

IF X IS A BGL-MODAL-DAY-COMPONENT
AND THE TIME-SLICE OF X IS Y
AND THE BGL-LEVEL OF X IS LOW
AND THE MINIMUM-PROBABILITY OF X \geq 0.2
AND THE IGNORANCE OF X < 1
THEN GENERATE-PROBLEM HYPOGLYCEMIA AT Y

This is motivated by the fact that such patients run a higher risk of hypoglycemia; therefore, physicians have to be able to detect all hypoglycemic episodes, even when the minimum probability of hypoglycemia is not very high, or when many data are missing: one single hypoglycemia episode would be enough to trigger this rule. The user can then choose whether to exploit only the results of the CBR classification step, if the output is considered reliable, or to analyze the ‘closest’ cases obtained through intra-class or inter-class retrieval. If this option holds, a second metarule states the application of the NN retrieval procedures. A test on the retrieved cases is performed; only cases whose protocol has the same injection number of the input case will be considered. Among them, the tool identifies the ones with a positive outcome (i.e. cases for which the applied protocol led to a low number of hypoglycemic events and to a HbA1c decreasing trend), on which it computes some descriptive statistics, thus setting the following parameters in the suggestion generation rule class:
- the number of insulin doses to be added or eliminated from the insulin plan to tackle a metabolic alteration;
- the overall variation in daily requirement;
- the quantitative variation in a single insulin dose.

The result of the earlier rule specialization is a list of refined suggestions; the suggestion selection and the protocol revision tasks are then performed as when the RBR system is run without integration (see Fig. 4).

CBR can also take advantage from the results of RBR; if the input case belongs to a competence gap region, and therefore, no suitable case could be retrieved to specialize the suggestion generation task, we have to run 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

![Fig. 4. The multi-modal reasoning structure.](image-url)
next periodical visit), a new case is learnt, and stored in the memory, to fill the competence gap.

3.4. Implementation

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) and a medical unit (MU). The MU assists the physician in the definition of the basal insulin regimen and diet through a periodic evaluation of the patient’s data, while the PU allows for automatic data collection and transmission from the patient’s house to the clinic. In particular, the MU is a web-based workstation in which several distributed servers cooperate in a transparent way to help the user in manage diabetes mellitus through: (i) consultation and analysis of the patients’ data; (ii) communication with patients’ home; (iii) decision support and internet-based repositories consultation. The core of the system is based on a web server written in COMMON LISP and called Lispweb [24]. The use of the Lispweb server allows the web-based application to exploit the full power of a high-level programming language, as well as any number of external services through the network communication facilities that it provides.

Lispweb makes it possible to create ‘secure’ applications while remaining in the context of web-based systems, with which physicians are nowadays familiar.

4. Results

To provide a first evaluation of the multimodal reasoning system performance, we resorted to an IDDM patient simulator, integrated in the T-IDDM architecture [25]. For each test, we defined a sample patient, whose features were extracted from a real pediatric patient in the case library. The simulator was run to generate 7 days of BGL measures (three measures per day plus some post-prandial data); to introduce intra-patient variability, the data were derived adding a 10% noise to the simulation results. By setting some parameters of the simulator, it was possible to reproduce the behavior of pediatric patients experiencing the problems described by our taxonomy. The RBR tool was run to stabilize the sample patient; the suggested protocol was acquired, and another monitoring period was simulated, in an iterative way, until the patient’s metabolism was stabilized. The same procedure was then applied to the multi-modal reasoning system, and its performances were compared with the RBR ones, in terms of number of adjustments required to reach normoglycemia.

As an example, we considered a girl of 14, with a weight of 40 kg and a height of 110 cm, a HbA1c value of 5.1% and an insulin requirement of 0.6 U/kg per day; her diabetes onset took place less than 1 year earlier. The input case was, therefore, classified by the CBR system as an example of clinical remission. From an analysis of the 23 cases retrieved from the clinical remission class, the integrated tool learnt to make a reduction in the dinner regular insulin dose up to 2 U. The RBR system, instead, worked on the default reduction of 1 U. Figs. 5 and 6, respectively, show the outcome of the RBR system and the one of the integrated approach. Being the RBR system more conservative, it took 2 weeks (i.e. two adjustments) to stabilize the simulated patient. On the other hand, the integrated approach, made more aggressive by rules specialization, just took one adjustment to produce the same result.
Moreover, we carried out an evaluation of the extended decision support functionality by resorting to real patients’ data, belonging to six pediatric patients enrolled at Policlinico S. Matteo hospital. Again the RBR and the multi-modal reasoning systems were compared on the same input situations. In 1999, 14 periodical visits took place for the six patients involved in the T-IDDM demonstration phase. In addition, the physicians made some adjustments to the therapy schemes between one visit and another. In our evaluation, each visit was considered as a case. When running the reasoner, each time we worked on a monitoring period during which the therapy scheme was kept unchanged, in order to avoid biases. Therefore, sometimes the same case referred to more than one period of monitoring data. Globally, we compared the multi-modal reasoning system to the RBR system over 37 monitoring periods. When running the multi-modal reasoning system, we first classified the case resorting to the taxonomy, then we performed the retrieval step. Inter-class retrieval was chosen when the probabilities of belonging to the classes at hand were very close (with a difference of 0.3 or less).

Some observations can be drawn from the table. In the majority of the situations, the multi-modal reasoning system proved to be more aggressive on hypoglycemia or on hyperglycemia, depending on what was the more relevant problem in the monitoring period at hand. This happened in 20 examples (54%). In 15 examples (40%) there was no
difference between the multi-modal reasoning and the RBR suggestions. This is still a positive result, as in those cases the RBR system was already aggressive enough, or the patient did not experience any problem, therefore, there were no suggestions (true for patient MM, who has a very good metabolic control). Finally, in two (5%) examples the performances of the multi-modal reasoning system were lower than the ones of the RBR system; such examples belong to the history of patient SC, referring to the visit that took place on 2/6/1999. An explanation of the failure can be the fact that such a visit belongs to a competence gap in the case library, only one case can be retrieved when running the CBR tool, but it is very peculiar, and therefore useless, as it reports a complete change in the therapy scheme structure, that does not apply in the present situation. Anyway, as explained before, the multi-modal reasoning system itself is able to face such limitation of the CBR paradigm, by finding a solution to a case belonging to a competence gap region through RBR, and storing the new example in the case library, thus making it more complete for future exploitation.

5. Final remarks

In clinical practice, the physician is provided with implicit knowledge (i.e. the operative knowledge stored in the HIS), and explicit one (i.e. formalized knowledge). Through CBR, by contextualizing the im-

Fig. 6. The 24 h profiles of blood glucose in response to the different therapeutic protocols proposed by the multi-modal reasoning system. The BGL values fall into the normality range just with one protocol revision (dash-dotted line).
Table 1  
Results of the comparison between the RBR and the multi-modal reasoning system performances of real patients’ data

<table>
<thead>
<tr>
<th>Case date</th>
<th>Patient</th>
<th>Classification</th>
<th>Monitoring period</th>
<th>Multi-modal versus RBR</th>
</tr>
</thead>
<tbody>
<tr>
<td>13/1/1999</td>
<td>LC</td>
<td>Stabilized metabolism/anorexia</td>
<td>25/1–10/3/1999</td>
<td>More aggressive on hypoglycemia</td>
</tr>
<tr>
<td>16/3/1999</td>
<td>LC</td>
<td>Stabilized metabolism/anorexia</td>
<td>15/5–31/5/1999</td>
<td>More aggressive on hypoglycemia</td>
</tr>
<tr>
<td>31/5/1999</td>
<td>LC</td>
<td>Stabilized metabolism/anorexia</td>
<td>31/5–21/6/1999</td>
<td>More aggressive on hypoglycemia</td>
</tr>
<tr>
<td>31/5/1999</td>
<td>LC</td>
<td>Stabilized metabolism/anorexia</td>
<td>21/6–2/7/1999</td>
<td>More aggressive on hypoglycemia</td>
</tr>
<tr>
<td>31/5/1999</td>
<td>LC</td>
<td>Stabilized metabolism/anorexia</td>
<td>16–28/8/1999</td>
<td>More aggressive on hyperglycemia still prompt to face hypoglycemia</td>
</tr>
<tr>
<td>9/9/1999</td>
<td>LC</td>
<td>Stabilized metabolism/anorexia</td>
<td>15–30/9/1999</td>
<td>No difference</td>
</tr>
<tr>
<td>8/6/1999</td>
<td>BD</td>
<td>Celiac disease</td>
<td>27/6–8/8/1999</td>
<td>No difference</td>
</tr>
<tr>
<td>25/1/1999</td>
<td>SC</td>
<td>Change life style/no motivation</td>
<td>26/1–3/3/1999</td>
<td>More aggressive on hyperglycemia</td>
</tr>
<tr>
<td>25/1/1999</td>
<td>SC</td>
<td>Change life style/no motivation</td>
<td>30/4–25/5/1999</td>
<td>More aggressive on hyperglycemia</td>
</tr>
<tr>
<td>2/6/1999</td>
<td>SC</td>
<td>Hormones/change life style/no motivation</td>
<td>2–20/6/1999</td>
<td>RBR is better</td>
</tr>
<tr>
<td>2/6/1999</td>
<td>SC</td>
<td>Hormones/change life style/no motivation</td>
<td>25/6–13/9/1999</td>
<td>RBR is better</td>
</tr>
<tr>
<td>13/9/1999</td>
<td>SC</td>
<td>No motivation</td>
<td>13/9–14/11/1999</td>
<td>More aggressive on hyperglycemia</td>
</tr>
<tr>
<td>22/3/1999</td>
<td>PM</td>
<td>Typical puberal problems</td>
<td>22/3–31/5/1999</td>
<td>No difference still prompt to face hypoglycemia</td>
</tr>
<tr>
<td>31/5/1999</td>
<td>PM</td>
<td>Hormones/typical puberal problem</td>
<td>31/5–11/6/1999</td>
<td>No difference still prompt to face hypoglycemia</td>
</tr>
<tr>
<td>31/5/1999</td>
<td>PM</td>
<td>Hormones/typical puberal problem</td>
<td>11–25/6/1999</td>
<td>More aggressive on hypoglycemia</td>
</tr>
<tr>
<td>3/4/1999</td>
<td>TA</td>
<td>Hormones/typical puberal problems</td>
<td>1/6–9/7/1999</td>
<td>More aggressive on hyperglycemia</td>
</tr>
<tr>
<td>9/7/1999</td>
<td>TA</td>
<td>Typical puberal problems</td>
<td>9/7–3/8/1999</td>
<td>More aggressive on hyperglycemia</td>
</tr>
<tr>
<td>27/9/1999</td>
<td>TA</td>
<td>Typical puberal problems</td>
<td>14/10–2/11/1999</td>
<td>More aggressive on hyperglycemia</td>
</tr>
<tr>
<td>20/1/1999</td>
<td>MM</td>
<td>Anorexia</td>
<td>20/1–2/2/1999</td>
<td>More aggressive on hyperglycemia</td>
</tr>
<tr>
<td>20/1/1999</td>
<td>MM</td>
<td>Anorexia</td>
<td>2/2–1/3/1999</td>
<td>No difference</td>
</tr>
<tr>
<td>20/1/1999</td>
<td>MM</td>
<td>Anorexia</td>
<td>1–23/3/1999</td>
<td>No difference</td>
</tr>
<tr>
<td>20/1/1999</td>
<td>MM</td>
<td>Anorexia</td>
<td>23/3–20/4/1999</td>
<td>No difference</td>
</tr>
<tr>
<td>20/4/1999</td>
<td>MM</td>
<td>Stabilized metabolism/anorexia</td>
<td>20/4–18/6/1999</td>
<td>No difference</td>
</tr>
<tr>
<td>20/4/1999</td>
<td>MM</td>
<td>Stabilized metabolism/anorexia</td>
<td>25/6–6/7/1999</td>
<td>No difference</td>
</tr>
<tr>
<td>6/7/1999</td>
<td>MM</td>
<td>Stabilized metabolism/anorexia</td>
<td>3–31/8/1999</td>
<td>No difference</td>
</tr>
<tr>
<td>31/8/1999</td>
<td>MM</td>
<td>Stabilized metabolism</td>
<td>31/8–26/10/1999</td>
<td>No difference</td>
</tr>
<tr>
<td>26/10/1999</td>
<td>MM</td>
<td>Stabilized metabolism</td>
<td>26/10–14/11/1999</td>
<td>No difference</td>
</tr>
</tbody>
</table>
plicit knowledge, and categorizing it resorting to the taxonomy, we are able to transfer the implicit knowledge into an explicit form, making it immediately exploitable by the physician. Moreover, defining a new therapy scheme for the situation at hand, as it would happen without the use of our methodology, is an activity of implicit knowledge creation; the new information is just stored in the HIS, but is not ready for reuse. Our system, instead, enables the physician to compare her own decision with the suggested therapy automatically; this decision assessment procedure transforms the new therapy into explicit knowledge, already analyzed in the light of both formalized information (due to the RBR component application) and past experience (due this time to the CBR component exploitation).

In the future, we plan to implement the following verification protocol [26] for the multi-modal reasoning system:

- two physicians, who never used the T-IDDM MU, will analyze the patients cases listed in Table 1;
- a third expert physician, again unfamiliar with T-IDDM, for each case, will compare the four available therapeutic prescriptions (two coming from her colleagues, one from the RBR system, and the other from the multi-modal reasoning system), without knowing who is the author of the various answers.

By applying such a methodology, we foresee to understand if the two T-IDDM decision support systems, and in particular the multi-modal reasoning one, mirror the reasoning of an expert diabetologist, other than those who provided the knowledge; we will be able to compare the T-IDDM reasoning tools performances between themselves, and also with the two physicians. At the same time we will test whether there are conflicting opinions among the physicians and we will find out in how many cases there is a complete interexpert consensus.

The overall T-IDDM service has been tested on 18 patients, from four European validation sites. The main outcomes of such demonstration phase were a reduction in the average value of HbA1c, and an intensification of the patient/physician interaction, leading in particular to more frequent therapy adjustments [27]. Such results, though conducted on few subjects, lead to the conclusion that the T-IDDM service can be a feasible system for telemonitoring a virtually large number of patients, following each of them more strictly with respect to standard clinical practice, thanks to the frequent data exchange with the patient’s house. In this way, insulin therapy can be better customized, thus leading to an improved metabolic control. Waiting for completing the verification protocol described in this section, what we can state by now is that, being the decision support functionality just one of the tools of the MU, the overall positive judgment on T-IDDM performances implicitly enforces a positive judgment on the reasoning functionality as well, and in particular on the multi-modal reasoning methodology described in this paper.

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References


