Case-based Reasoning for Medical Knowledge-based Systems

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Abstract

In many domains Case-based Reasoning (CBR) has become a successful technique for knowledge-based systems. In medical domains, attempts to apply the complete CBR cycle are rather exceptional. Some systems have recently been developed, which on the one hand use only parts of the CBR method, mainly the retrieval, and on the other hand enrich the method by a generalisation step to fill the knowledge gap between the specificity of single cases and general rules. So, in this paper we discuss the appropriateness of CBR for medical knowledge-based systems, point out problems, limitations and possibilities how they can partly be overcome.

1. Introduction

Case-based Reasoning (CBR) has become a successful technique for knowledge-based systems in many domains, while in medical domains some more problems arise to use this method. We are going to discuss the appropriateness of CBR for medical knowledge-based systems, point out problems, limitations and possibilities how they can partly be overcome.

Case-based Reasoning means to use previous experience in form of cases to understand and solve new problems. A case-based reasoner remembers former cases similar to the current problem and attempts to modify their solutions to fit for the current case (Fig.1. shows the Case-based Reasoning cycle developed by Aamodt [1]). The underlying idea is the assumption that similar problems have similar solutions. Though this assumption is not always true, it holds for many practical domains.

CBR consists of two main tasks [1, 2]: The first is the retrieval, which is the search for or the calculation of most similar cases. If the case base is rather small, a sequential calculation is possible, otherwise faster non-sequential indexing [2, 3] or classification algorithms (e.g. ID3 [4] or Nearest Neighbor match [5]) should be applied. For this task much research has been undertaken in the recent years and actually it has become correspondingly easy to find sophisticated CBR retrieval algorithms adequate for nearly every sort of application problem.

The second task, the adaptation (reuse and revision) means a modification of solutions of former similar cases to fit for a current one. If there are no important differences between a current and a similar case, a simple solution transfer is sufficient. Sometimes only few substitutions are required, but sometimes the adaptation is a very complicated process. So far, no general adaptation methods or algorithms have been developed; the adaptation is still absolutely domain dependent.

Why Case-based Reasoning for medical decision making ?

Especially in medicine, the knowledge of experts does not only consist of rules, but of a mixture of textbook knowledge and experience. The latter consists of cases, typical and exceptional ones, and the reasoning of physicians takes them into account [6]. In medical knowledge based systems there are two sorts of knowledge, objective knowledge, which can be found in textbooks, and subjective knowledge, which is limited in space and time and changes frequently.

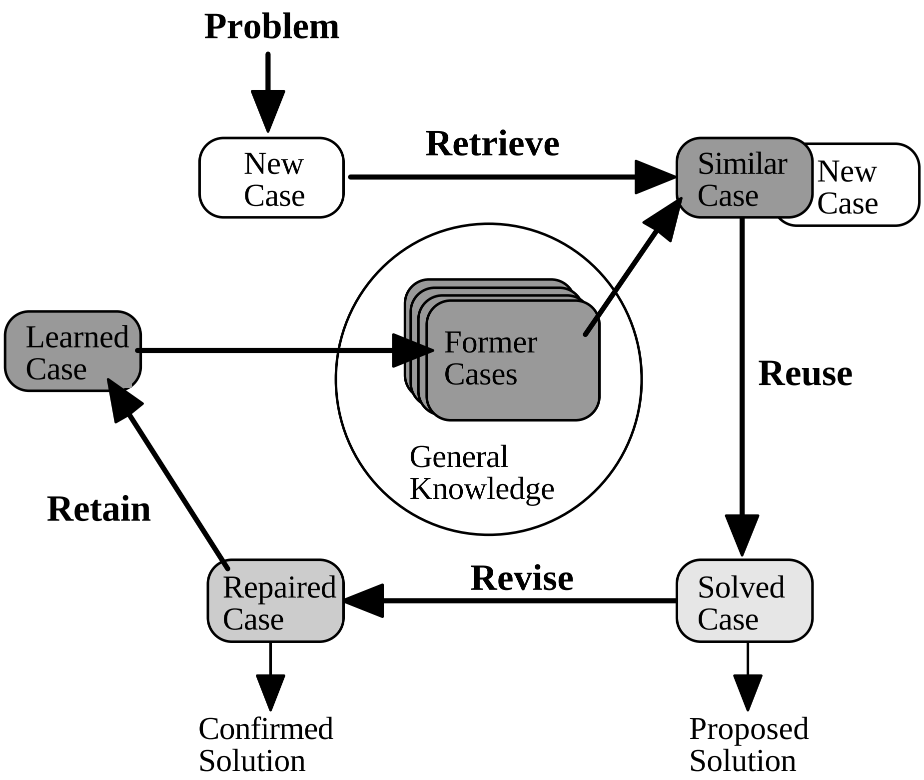

Figure 1. The Case-based Reasoning cycle developed by Aamodt

The problem of updating the changeable subjective knowledge can partly be solved by incrementally incorporating new up-to-date cases [6]. Both sorts of knowledge can clearly separated: Objective textbook knowledge can be represented in forms of rules or functions, while subjective knowledge is contained in cases.

So, the arguments for case-oriented methods are as follows:

1. Reasoning with cases corresponds with the decision making process of physicians.
2. Incorporating new cases means automatically updating parts of the changeable knowledge.
3. Objective and subjective knowledge can be clearly separated.
4. As cases are routinely stored, integration into clinic communication systems is easy.

2. Medical Case-based Reasoning systems

In medicine, CBR has mainly been applied for diagnostic and partly for therapeutic tasks. Related methods have been used in further fields, case-oriented methods for tutoring (e.g. D3 [7]) and retrieval methods to search for similar images (e.g. MACRAD [8]). So, here we first present three diagnostic and systems; further systems are mentioned in [9].

One of the earliest medical expert systems that uses CBR techniques is CASEY [10]. It deals with heart failure diagnosis. The system uses three steps: A search for similar cases, a determination process concerning differences and their evidences between a current and a similar case, and a transfer of the diagnosis of the similar to the current case or - if the differences between both cases are too important - an attempt to explain and modify the diagnosis. If no similar case can be found or if all modification attempts fail, CASEY uses a rule-based domain theory. The most interesting aspect of CASEY is the ambitious attempt to solve the adaptation task by general adaptation operators. However, as many features have to be considered in the heart failure domain and as consequently many differences between cases can occur, not all differences between former similar and current cases can be handled by the developed general adaptation operators.

The FLORENCE system [11] deals with health care planing in a broader sense, for nursing, which is a less specialised field. It fulfils all three basic planing tasks: diagnosis, prognosis, prescription. Diagnosis is not used in the common medical sense as the identification of a disease, but it seeks to answer the question: „What is the current health status of this patient?“ Rules concerning weighted health indicators are applied. The health status is determined as the score of the indicator weights. Prognosis seeks to answer the question: „How may the health status of this patient change in the future?“ Here a Case-based approach is used. The current patient is compared to a similar previous patient for whom the progression of the health status is known. Similar patients are searched for first concerning the overall status and subsequently concerning the individual health indicators. As the further development of a patient not only depends on his situation (current health status, basic and present diseases), but additionally on further treatments, several individual projections for different treatments are generated. Prescription seeks to answer the question „ How may the health status of this patient be improved?“ The answer is given by utilising general knowledge about likely effects of treatments and also by considering the outcome of using particular treatments in similar patients. That means it is a combination of a rule-based and a case-based approach.

The most interesting aspect of MEDIC [12] is its memory organisation. MEDIC is a schema-based diagnostic reasoner on the domain of pulmonology. Schemata represent the problem solvers knowledge. These are packets of procedural knowledge about how to achieve a goal or a set of goals. The memory does not only consist of schemata, but additionally of diagnostic memory organisation packets of individual cases of diagnosis and of scenes. A scene represents an instantiation of a schema in a particular case. This memory organisation and retrieval allows a reasoner to find the most specific problem-solving procedures available.

3. Problems of Case-based Reasoning for medical applications

To use Case-based Reasoning a few problems have to be solved: A representation form for cases has to be determined, an appropriate retrieval algorithm has to be selected and an infinite growth of the case base has to be avoided e.g. by clustering cases into prototypes and removing redundant cases or by restricting the case base to a fixed number of cases and updating the case base during an expert consultation session [8], but the main problem of Case-based Reasoning is the adaptation task. Little research has been undertaken on this topic and only formal adaptation models [13], but no general methods have been developed so far. The adaptation still depends on domain and application characteristics. Sometimes no adaptation is necessary, because e.g. the field and the cases are as unspecialised as in FLORENCE, sometimes the adaptation is a simple solution transfer or only a little bit more, sometimes just a few constraints have to be checked (e.g. GS.52), but sometimes many differences between current and former similar cases have to be considered (e.g. CASEY). The latter situation is not only a problem for medical applications. However, in medicine it increases, because cases often consist of an extremely large number of features. In non-medical CBR applications, the adaptation is usually solved by a set of specific adaptation rules, which usually have to be acquired during expert consultation sessions. As these rule sets have to consider all possible important differences between current and former similar cases, for medical applications it is mostly impossible to generate such sets. So, some adaptation solutions have been developed that are not limited to, but are rather typical for medical domains.

Focusing on retrieval. An idea to avoid the adaptation problem is to build retrieval-only systems. These are programs that only retrieve similar cases and present them as information to the user. Some of them additionally point out important differences between current and similar cases. The justification for giving up the adaptation task is that in some application domains it is much too complicated or even impossible to acquire adaptation knowledge [14] and that physicians are interested to get information about former similar cases, but wish to reason for current patient themselves [8]. Examples of succesful retrieval-only systems are mainly in the fields of images [8] and of organ function courses [15].

A similar idea is to combine CBR with rule-based methods. In CASEY [10] this combination is extremely lose: If no similar case can be found or if not all adaptation problems can be solved, a separate rule-based program is applied. However, in some systems there are much closer relations between a CBR component and other components. In CARE-PARTNER [16] CBR retrieval is used to search for similar cases to support evidences for a rule-based program. In a program for decision making for insulin dependent diabetic mellitus patients [17] a CBR part and a rule-base are applied in parallel, the results and the co-ordination of further steps is handled by meta-rules. However, these systems do not perform the complete CBR cycle, but only incorporate CBR retrieval.

Generalised cases. As one reason for the adaptation problem is the extreme specificity of single cases, a different idea is to generalise from single cases into abstracted prototypes [18] or classes [19]. Though the main ideas for this generalisation are to structure the case base, to decrease the storage amount by erasing redundant cases, to speed-up the retrieval and sometimes to learn more general knowledge, additionally it can at least partly help to solve the adaptation problem. An example is the diagnostic system for dysmorphic syndromes (GS.52), where each case is characterised by a list of features, which usually contains between 40 and 130 symptomes and syndromes. This means, there are so many differences between a current and a similar case that an adaptation that takes all of them into account is impossible. So, for all cases with the same dysmorphic syndrome a prototype is created, which contains the most frequent observed features of these cases. Such an abstracted prototypical case represents a dysmorphic syndrome and usually contains only up to 20 features. For a current case the most similar prototypes are calculated. Subsequently, for the adaptation only few constraints have to be checked.

The idea to partly solve the adaptation task by generalising can only work for diagnostic tasks where abstracted typical cases represent diagnoses and additional specific features of former single cases can be neglected. Abstracted cases fill the gap between general rules and specific cases. If a hierarchy of abstracted cases exists (as in MEDIC), adaptation can be seen as a top down search to find the most specific case that fits the current problem [13].

4. Examples

4.1. Retrieval-Only: Time Course Prognoses of the Kidney Function

As intensive care patients are often no longer able to maintain adequate fluid and electrolyte balances due to impaired organ functions or because they are ventilated, physicians need objective criteria for the monitoring of the kidney function and to diagnose therapeutic interventions as necessary. At our intensive care unit the renal function monitoring system NIMON [21] was developed that daily prints a renal report that consists of 13 measured and 33 calculated parameter values. However, the interpretation of all reported parameters is quite complex and needs special knowledge of the renal physiology. Our aim was to develop a system, called ICONS [15], that gives an automatic interpretation of the renal state to elicit impairments of the kidney function on time. In the domain of fluid and electrolyte balance, neither prototypical courses in ICU settings are known nor exists complete knowledge about the kidney function. So we had to design our own method to deal with course analyses of multiple parameters without prototypical courses and without a complete domain theory.

The method consists of three main steps: Two data abstractions plus CBR retrieval. We have got the idea of abstracting many parameters into one single parameter from RÉSUMÉ [22] where the course of this single parameter is analysed by means of a complete domain theory. The comparison of parameter courses with well-known course pattern is performed in some medical knowledge based systems (e.g. by Haimowitz and Kohane [23] and in VIE-VENT [24]). As no such pattern are yet known for the kidney function, we use single courses and incremently learned prototypes instead of well-known course pattern to compare with. We attempt to learn course pattern by structuring the case base by prototypes.

As the interpretation of all NIMON parameters is too complex, we decided to abstract them. For this data abstraction we have defined states of the renal function which determine states of increasing severity starting with a normal kidney function and ending with a renal failure. Based on these definitions, we ascertain the appropriate state of the kidney function per day. Based on the sequence of assessments of transitions of the state of a day to the state of the respectively next day, we generate four different trends. These trends describe courses of states. Subsequently, we use Case-Based Reasoning retrieval to search for similar courses. We present the current course in comparison to similar ones to the user, the course continuations of the similar courses serve as prognoses (Fig.2.). As there may be too many different aspects between both patients, the adaptation of a similar to the current course is not done automatically. ICONS [15] offers only diagnostic and prognostic support, the user has to decide about the relevance of all displayed information (e.g. additional renal syndromes and courses of single kidney function parameter values).

Retrieval

The parameters of the trend descriptions are used to search for similar courses. As the aim is to develop an early warning system, a prognosis is needed. As there are many different possible continuations for the same previous course, it is necessary to search for similar courses and different projections. Therefore, we have divided the search space into nine parts corresponding to the possible continuation directions within three days. Each direction forms an own part of the search space. During the retrieval these parts are searched separately and each part may provide at most one similar course. The retrieval consists of two steps for each projection part. First we search with an activation algorithm [25] concerning qualitative features. Subsequently, we check the retrieved cases with an adaptability criterion that looks for sufficient similarity, since even the most similar course may differ from the current one significantly. If several courses are selected in the same projection part, in a second step a sequential similarity measure concerning the quantitative features is used. It is a variation of TSCALE [26] and goes back to Tversky [27].

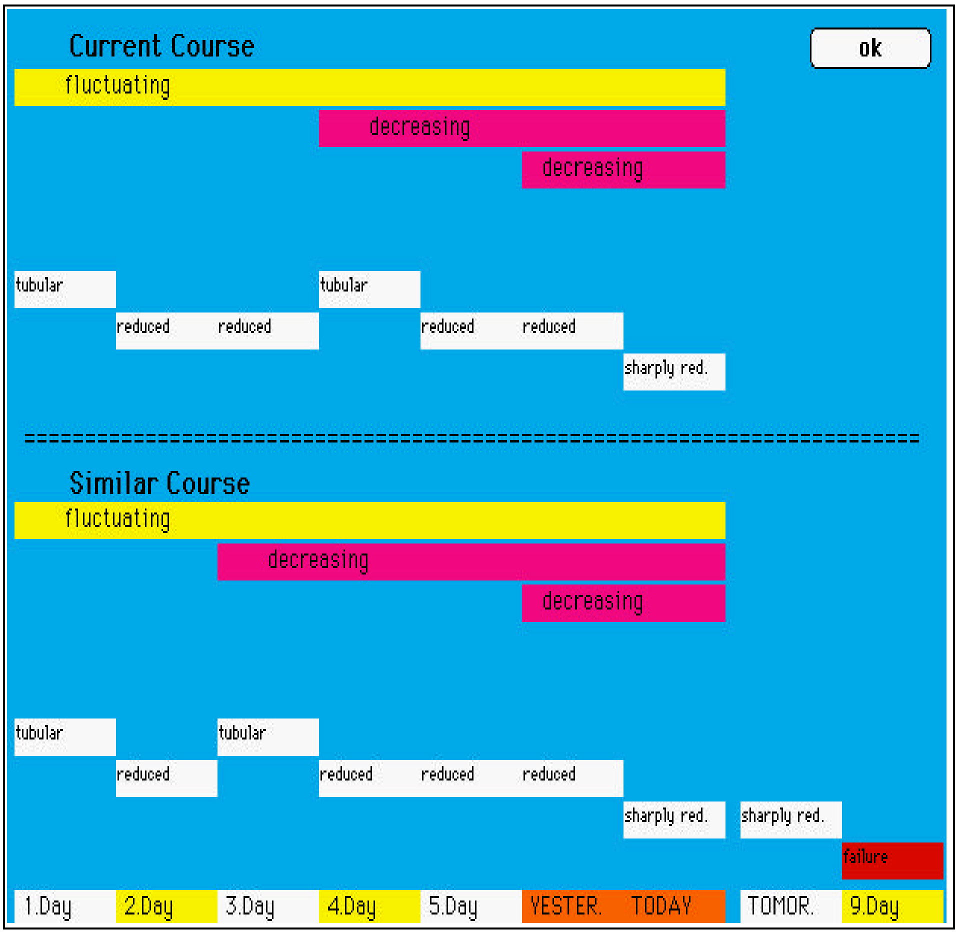

Figure 2. Comparative presentation of a current and a similar course. In the lower part of each course the (abbreviated) kidney function states are depicted. The upper part of each course shows the deduced trend descriptions.

4.2. Dysmorphic Syndromes

GS.52 [20] is a prototype-based expert system which is routinely used in the children's hospital of the University of Munich for many years. It is a diagnostic support system for dysmorphic syndromes. Such a syndrome means a non-random combination of different disorders. The major problems are the high variability of the syndromes (hundreds), the high number of case features (between 40 and 130) and the continuous knowledge modifications of dysmorphic syndromes. Each syndrome is represented by a prototype that contains its typical features (Table 1).

The prototypes are acquired by an expert consultation session. The physician selects a new or an existing syndrome and typical cases for this syndrome. Subsequently, GS.52 determines the relevant features and their relative frequencies.

The diagnostic support occurs by searching for the most adequate prototypes for a current case. A similarity value between each prototype and the current case is calculated and the prototypes are ranked according to these values.

Diminished postnatal growth rate	77%	Anteverted nares	63%
Hypercalcaemia	30%	Prominent lips	17%
Prenatal onset	75%	Long philtrum	17%
Mild microcephaly	67%	Fullness of peri-o. region	75%
Full cheeks	46%	Medial eyebrow flare	25%

Table 1. Portion of an example of a generated prototype. The numbers are the relative frequency in percentages the features occured in the cases of the prototype.

We evaluated the similarity measure of Tversky and the measure of Rosch and Mervis. Tversky [27] determines the similarity between a case and a prototype by adding up the number of shared features and subtracting the number of features of the prototype which the case does not share and subtracting the number of features the case does not share with the prototype. In contrast to him Rosch and Mervis [28] ignore those case features which the prototype does not share. Our experiment with both measures (Fig. 3.) shows that their measure performed better than Tversky's, which indicates to ignore those features of the current case the prototype under consideration does not share.

The result additionally indicates to present more probable syndromes rather than to produce the one and only diagnosis. For both measures the correct diagnosis was always among the first ten, mostly among the first five and majoritiely the first position. GS.52 contains about 230 diagnoses and more than 800 symptoms.

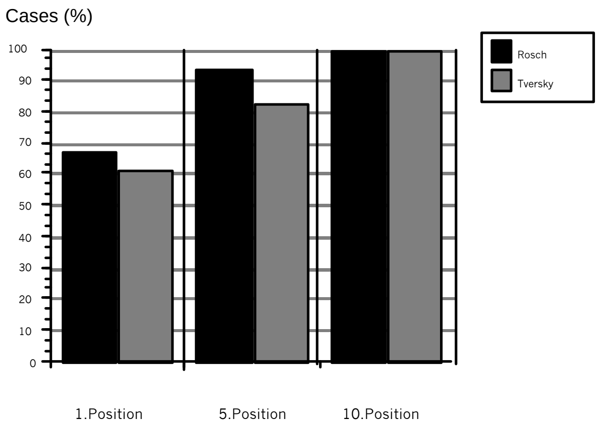

Figure 3. Sensivity of GS.52 using cases of trisomy-21

GS.52 differs from typical CBR systems, because cases are clustered into prototypes, which represent diagnoses, and the retrieval searches only among these prototypes. The sequential retrieval considers every prototype, calculates a similarity value for each prototype and ranks them according to these values. The adaptation consists of two examinations of the probable prototypes: A plausibility check with general rules (constraints) and a check of evidences for specific syndromes (some syndromes are nearly a proof for or against some diagnoses).

5. Conclusion

Case-based Reasoning seems to be a suitable technique for medical knowledge based systems. However, the adaptation task is the bottleneck that has to be solved. Though adaptation is sometimes a rather easy task (as in FLORENCE), in medical application it may become an insurmountable difficulty. In this paper we have presented three possible solutions, all of them are justified for specific applications and none of them is an ultimate solution. Retrieval-only systems are especially useful for visualisation tasks, e.g. of images or organ function courses, because the users wish to see and interpret all specific details themselves [8]. Solving the adaptation by generalising is restricted to diagnostic problems where the condition holds that: The more abstracted a case the more typical are its features. This means to adapt by searching top down in a hierarchy of abstracted cases, the further down the cases are placed in the hierarchy, the more specific and less typical are their additional features [13]. Combining CBR with rule-based components should not really be seen as a solution for the adaptation problem, but as an opportunity to incorporate CBR subtasks (mainly the retrieval) into rule-based programs instead of applying the complete CBR cycle.

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Using Induction Trees to Do Case Adaptation in Case-Based Reasoning

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Abstract. Case-based reasoning is a problem solving method that uses previous experiences to solve new problems. It comes up with new solutions by adapting old ones that have successfully solved previous problems similar to the given ones. Most current CBR systems use context-dependent adaptation knowledge to do case adaptation; no general methods or algorithms have been proposed for case adaptation so far. Adaptation is still one of the main bottlenecks in case-based reasoning. This paper proposed a general framework to do case adaptation. It contains two modules, namely, a case selection and a case adaptation. The case selection module induces an induction tree from the features of the retrieved candidate cases and employs decision theory to calculate the expected utility for each feature. Feature adaptability is also solved in the calculation of utility. Thus, higher utility implies higher adaptability. It employs the knowledge-based planning mechanism to create a case adaptation plan consisting of a set of adaptation methods form the library. Execution of the plan generates solution adapted to the given problem. The case adaptation architecture can work as a subsequent component of any case retrieval component to constitute a complete case-based reasoning system.

1. Introduction

Medical diagnosis from surface etiology is difficult since there involve lots of complications. A clinician has to carefully investigate a patient's symptoms, chief complaints, and pathology examination in order to decide possible diseases. It takes years of training and practice for a physician to make correct decisions. This worsens when the related etiology is hard to discern or multiple diseases suffered. The rapidly growing medical knowledge and new patient cases make the diagnosis process even more difficult. Updating the medical knowledge incrementally in a traditional medical diagnosis system to cope with this is not that easy [3]. It can be made easier and reliable, however, if supplied with a system that contains and provides recommendations from the past diagnosis cases of different morbidity, since the clinician can benefit a lot from these prior cases. This implies that the case-based reasoning (CBR) approach is appropriate to the problem.

CBR is a problem solving method that uses previous experiences to solve new problems [3]. It has long been applied in medicine [1, 2, 5, 6]. It comes up with new diagnosis by adapting old ones that have successfully solved previous cases similar to the given patient data. Most CBR systems, however, use context-dependent adaptation knowledge to do case adaptation. So far, no general methods or algorithms for case adaptation have been proposed. Adaptation is still one of the major bottlenecks in CBR.

This paper proposes a general framework to do case adaptation. It contains two modules, namely, a case selection and a case adaptation. The case selection module creates an induction tree from the morbid features of the retrieved candidate cases and calculates the expected utility for each morbid feature. We elaborately include feature adaptability in the calculation of utility. Thus, higher utility implies higher adaptability. The utility is used to conduct pruning on the induction tree. The case adaptation module then follows the pruned induction tree to create a case adaptation plan consisting of a set of feature adaptation plans. Execution of the case adaptation plan proposes a new diagnosis.

2. System Architecture

Fig. 1 is the architecture of case adaptation. It contains two modules, i.e., case selection and case adaptation. The case selection uses induction tree to classify candidate cases and induces feature values. First, it induces an induction tree from the features of the candidate cases. It also calculates expected utility for each feature to analyze the usefulness of each feature. It then prunes the induction tree according to the expected utility and solves the constraints and causal relations.

The case adaptation module does actual adaptation by following the induction tree, supported by the adaptation plan library. The basic adaptation strategy is as follows. It first creates a subtree from the induction tree, called adaptation tree, that covers all the problem features, satisfies all the relevant constraints, and contains no nodes whose expected utilities are below a threshold. It also checks for those features that contain no values in the candidate case. It then selects a feature adaptation plan for each node in the adaptation tree from the adaptation plan library. It finally produces an adapted case severing as the diagnosis for the patient data by executing the case adaptation plan. This may involve the manipulation of feature values that appear in multiple paths, i.e., multiple diseases. The following detail each module.

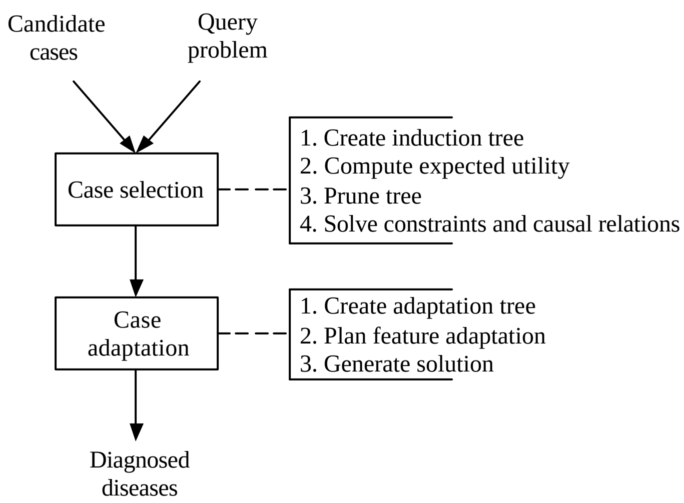


Fig. 1 System architecture

3. Case Selection

The case selection module does refinement on the retrieved candidate cases, which all contain some features that are somewhat related to the characteristics of the given patient data. Inducing all candidate cases into an induction tree, which is a decision tree with constraint links, provides a tool for guiding the selection of most possible diagnoses. Fig. 2 exemplifies an induction tree with 3 candidate cases (Table 1) for respiratory disease diagnosis. Note that each non-terminal node represents a morbid feature of the candidate cases. Each outgoing link from a node represents a value for the represented feature. The case selection component then goes to analyze the usefulness of the features by calculating their expected utilities. The calculation, basically, compares the difference of the context of the feature value with the given patient data and estimates the adaptability of the morbid feature accordingly. The adaptability is then used to calculate an expected utility (EU) by Equ. (1) for the feature. EU serves as a metric for selecting cases for adaptation.

$$EU(A_j) = \sum_{k=1}^{n} EU(A_{jk}) * AD(A_j \to A_{jk}) * P(A_j \to A_{jk}), \tag{1}$$

where A_{jk} stands for the kth child node of feature node A_j , n is the number of children of feature node A_j , $AD(A_j \to A_{jk})$ is the adaptability value of the feature value represented by link $A_j \to A_{jk}$ [4], and $P(A_j \to A_{jk})$ stands for the probability of the feature value represented by link $A_j \to A_{jk}$ defined in Equ. (2).

$$P(A_j \to A_{jk}) = \frac{N(A_j \to A_{jk})}{\sum_{m=1}^{n} N(A_j \to A_{jm})}, \tag{2}$$

where $N(A_j \to A_{jk})$ is the occurrences of $A_j \to A_{jk}$, n is the number of siblings, and k is the kth sibling of A_j, $1 \le k \le n$.

Table 1 Example candidate cases

	Case #1	Case #2	Case #3
Personal history 1 (PH1)	Pneumonia	Asthma	N/A
Personal history 2 (PH2)	Typhoid	Emphysema	N/A
Chief complaint (CC)	Cough	Cough	Cough
Present illness 1 (PI1)	Sputum	Hemoptysis	Hemoptysis
Present illness 2 (PI2)	Fever	Fever	Dyspnea
Present illness 3 (PI3)	Chest pain	Weight loss	Chest pain
Present illness 4 (PI4)	Chill	Night sweating	Weight loss
Temperature (Temp)	39.1°C	38.2°C	N/A
Pulse rate (PR)	68 (/min)	72 (/min)	N/A
Respiratory rate (RR)	18 (/min)	20 (/min)	N/A
Blood pressure (BP)	130/85 (mmHg)	120/80 (mmHg)	N/A
Hb (HB)	16 (g/dl)	15 (g/dl)	N/A
RBC (RBC)	$4.3*10^6$	$4.5*10^6$	N/A
WBC (WBC)	$20*10^3$	$18*10^3$	N/A
Thoracentesis (TH)	N/A	N/A	Effusion
Effusion protein (EP)	N/A	N/A	4.6 (g/dl)
Specific gravity (SG)	N/A	N/A	1.4
Cultures (CU)	Haemophilus	M. tuberculosis	N/A
Cytology (CY)	Negative	Negative	N/A
Chest x-ray (CXR)	Normal	Cavitation	N/A
Disease type (DT)	Respiratory	Respiratory	Respiratory
Affected organ (AO)	Pulmonary	Pulmonary	Pulmonary
Diagnosis (DI)	Bacterial pneumonia	Tuberculosis	Pleural effusion

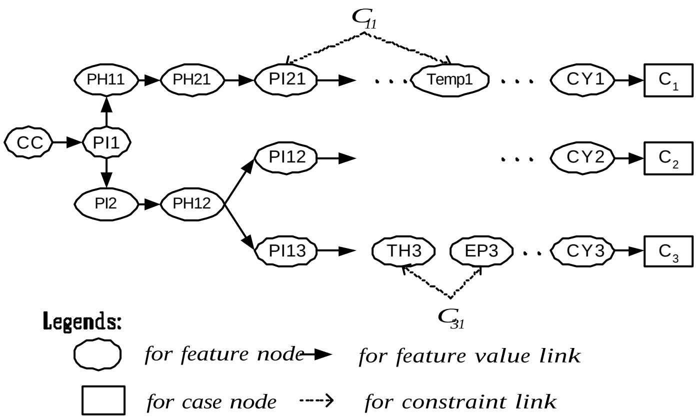
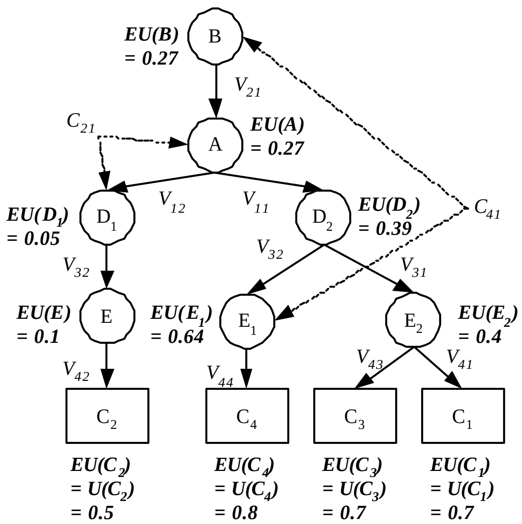


Fig. 2 Induction tree

The calculation process of expected utility starts by setting the expected utility of the leaf node C_i to C_i's similarity, i.e., $EU(C_i)=S_i$, where S_i represents the similarity of case C_i to the given problem p [8]. $EU(C_i)$ is then backed up to its father node by Equ. (1) to compute its father's expected utility. This process repeats until it reaches the root node. Fig. 3 exemplifies the computation. Note that each leaf of the induction tree stores the surface feature similarity of each candidate case. One interesting characteristic of this tree is that feature values that appear in more candidate cases are grouped more closely to the root for easy and fast subsequent inspection.



Link	Value	Adaptability	Probability
$B \rightarrow A$	V_{21}	1.0	1.0
$A \rightarrow D_1$	V_{12}	0.6	0.33
$A \rightarrow D_2$	V_{11}	1.0	0.67
$D_1 \rightarrow E$	V_{32}	0.5	1.0
$D_2 \rightarrow E_1$	V_{32}	0.8	0.57
$D_2 \rightarrow E_2$	V_{31}	0.6	0.43
$E \rightarrow C_2$	V_{42}	0.2	1.0
$E_1 \rightarrow C_4$	V_{44}	0.8	1.0
$E_2 \rightarrow C_3$	V_{43}	0.6	0.67
$E_2 \rightarrow C_1$	V_{41}	0.5	0.33

Fig. 3 Example of expected utility computation

Finally, it prunes the nodes whose EU are below a threshold and re-arranges the nodes that are under constraints into a proper causal sequence [7].

4. Case Adaptation

The basic strategy to do case adaptation contains three steps, namely, adaptation tree creation, adaptation plan generation, and adaptation plan execution. First, it creates a subtree from the induction tree, called adaptation tree, that covers all the problem features, satisfies all the relevant constraints, and contains no nodes whose expected utilities are below a threshold. It also checks for those features that contain no values in the candidate case. It computes and uses the following *closeness* measurement to decide how to adapt the case.

$$Closness(A_j \rightarrow A_{jk}) = P(A_j \rightarrow A_{jk}) * PR_i(A_j \rightarrow A_{jk}),$$

where $P(A_j? A_{jk})$ is the occurrence probability of the feature value $A_j? A_{jk}$ and $PR_i(A_j? A_{jk})$ is the proximity of the feature value $A_j? A_{jk}$ to the disease type *i*. If the closeness is above a threshold, the corresponding feature value in the candidate case is considered to be relevant to the new problem and retained in the adaptation tree. In this case, the judged disease is stated to be true "under the condition that the feature value $A_j? A_{jk}$ occurred, i.e., **IF** $(A_j? A_{jk})$ **THEN** (diseases)". If the closeness is below the threshold, the corresponding feature value as well as the associated constraints is removed. This strategy of handling null feature values in adaptation can reduce most user intervention. Fig. 4 shows the adaptation tree created from Fig. 2.

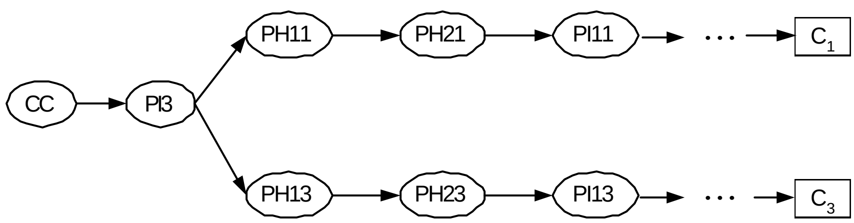
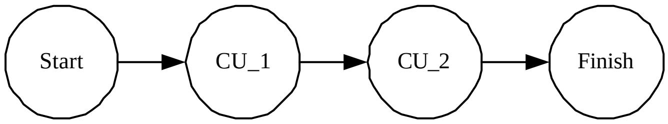


Fig. 4 Adaptation tree

Second, the adaptation process develops a case adaptation plan from the adaptation tree with the help of a feature adaptation plan library by creating a feature adaptation plan for each one. A feature adaptation plan specifies how to adapt a feature value. If none of such feature adaptation plan exists, a partial-order planning planner is called to produce a new feature adaptation plan from the general adaptation operators of the plan library for the feature. Fig. 5 illustrates the feature adaptation plan for the *culture* feature, which adapts the value from haemophilus to pneumocuccus.



Step #	Start	CU_1	CU_2	Finish
Feature name	CU_1	CU_1	CU_1	CU_1
Feature value	Haemophilus	V_{CU1}	Pneumocuccus	Pneumocuccus
Adaptation operator	N/A	Problem abstraction	Problem refinement	N/A

Fig. 5 Feature adaptation plan for the "culture" feature

Finally, the adaptation process follows the case adaptation plan to adapt the feature values in the adaptation tree to meet the patient data in order to produce a new diagnosis. If there are multiple paths in the adaptation tree, each path has to be visited in order to take care of multiple solutions.

5. Conclusions

We have proposed a general case adaptation mechanism that can be used in medical diagnosis based on the induction tree technique to handle the adaptation problem in CBR. It features the integration of induction technology with utility theory in case selection, which helps a lot in hammering out valuable morbid features for the target case from existent ones and in pruning unnecessary search space. It also employs the general planning technique to create a case adaptation plan that contains a set of general adaptation methods form the library. The diagnosis for the given case is obtained by executing the case adaptation plan. This general adaptation architecture can work as a subsequent component of any case retrieval component to constitute a complete CBR system.

In summary, the proposed general adaptation architecture exhibits the following interesting features. First, the case adaptation is effective with the help of feature expected utilities. It also dynamically tackles multiple cases with the help of the adaptation tree. Second, the adaptation process is a planning-based mechanism, which is thus unlikely to be performance-degraded. It can select the adaptation plan automatically without any domain-dependent heuristics to specify the adaptation methods. Finally, the general adaptation plan library can support the planning-based adaptation process and also assimilate adaptation plan to enhance the adaptation ability.

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Managing diabetic patients through a Multi Modal Reasoning methodology

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Abstract

We propose a Multi Modal Reasoning (MMR) methodology meant to provide physicians with knowledge management and decision support functionality in the context of Insulin Dependent Diabetes Mellitus care. The MMR system performs a tight integration of Case Based Reasoning (CBR), Rule Based Reasoning (RBR) and Model Based Reasoning (MBR), with the aim of suggesting a therapy properly tailored on the patient's needs, overcoming the single approaches limitations. This methodology allows the exploitation of the implicit knowledge embedded in patients' visits (past cases) and in monitoring data, respectively through Case Based retrieval and model identification. On the other hand the explicit domain knowledge is formalised in a set of production rules, and in the resulting model itself. The system has been preliminary tested on real patients' data.

1. Introduction

The introduction of Hospital Information Systems (HIS) into clinical practice has led to the memorisation 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. In the field of chronic diseases, and in particular of Insulin Dependent Diabetes Mellitus (IDDM) care, the quantity of data is huge, since the illness is a life-long condition. IDDM patients suffer from an impaired functionality of the pancreatic beta cells, and need to inject themselves exogenous insulin 3 to 4 times a day to regulate blood glucose metabolism. Such an intensive therapy may lead to hypoglicemic episodes: Blood Glucose Level (BGL) has therefore to be frequently tested and logged. In order to improve the quality of care, this implicit knowledge about patients' histories (and physicians' expertise) needs to be kept, managed and distributed across the institution, and to be integrated with the other available knowledge sources, i.e. the explicit domain knowledge, formalised in knowledge bases or rule sets. A proper Knowledge Management (KM) approach seems a valuable way for supporting the complex process of IDDM patients management. In particular it seems interesting to provide instruments for supporting decisions in therapy planning, since revising insulin administration is a complex task, that can be correctly afforded only by customising general indications on the basis of the single patient's features [1].

To this end, we propose a Multi Modal Reasoning (MMR) methodology, that performs a tight integration of Case Based Reasoning (CBR), Rule Based Reasoning (RBR) and Model Based Reasoning (MBR), with the aim of suggesting a therapy properly tailored on the patient's needs, overcoming the single approaches limitations. The methodology allows the exploitation of the implicit knowledge embedded in patients' visits (past cases) and in monitoring data, respectively through Case Based retrieval and model identification. On the other hand the explicit domain knowledge is formalised in a set of production rules, and in the resulting model itself.

2. The Multi Modal Reasoning paradigm

The backbone structure of the decision support procedure we have implemented is based on the following reasoning tasks:

1. identification of metabolic problems;
2. generation of a set of suggestions, able to cope with the identified metabolic problems, and selection of the most suitable ones;
3. application of the selected suggestions to the current insulin protocol;
4. selection of additional library protocols that could also fit the situation at hand.

The reasoning paradigm described above is completed resorting to the combination of a rule system, a Case Based retrieval system, and a model of the glucose-insulin interaction. In particular, the RBR system is able to schedule the tasks execution, invoking the different methods to be exploited. In the following subsections, the tasks execution is described in detail.

2.1 Identification of metabolic problems

The RBR system fires some specialised procedures for data analysis and metabolic indicators extraction. All the data collected during daily home monitoring by diabetic patients are classified as belonging to one of seven non-overlapping time slices, in which the day is subdivided, i.e. breakfast, mid-morning, lunch, mid-afternoon, dinner, bed time, night time. The data are then analysed through a Temporal Abstractions (TA) technique [2]. The basic principle of TA methods is to move from a time-point to an interval-based representation of the data. Given a sequence of time stamped data (events), the adjacent observations which follow meaningful patterns are aggregated into intervals (episodes). In particular, *basic* abstractions can be used to extract *states* (episodes of low, high, normal values) from a time series. When detecting state patterns in time series of numerical variables, a preliminary qualitative abstraction is carried out. The mapping between the qualitative abstractions and the quantitative levels of each numerical variable depends on the time slice and on the specific patient’s characteristics. For example, the BGL normal range is wider in the morning than around lunch, and it is wider in paediatric patients than in adult ones. Then, the BGL state abstractions are derived, moving from the original time scale to a new scale obtained from the sequence of relevant patterns detected in the data.
In our application, five BGL state abstractions have been defined: severe hypoglycemia, mild hypoglycemia, normoglycemia, mild hyperglycemia, and severe hyperglycemia. From these episodes, the so-called BGL modal day can be calculated [2]. The BGL modal day is an indicator able to summarise the average response of the patient to a certain therapy. By applying the Bayesian updating scheme described in [3], in each time slice we derive an interval probability estimate for the marginal distributions of the five BGL states.
The difference between the lower and upper probability bounds is proportional to the number of missing data, i.e. the number of days in which the patient did not collect the data in a certain time slice, over a certain monitoring period. The formulas for calculating the probability bounds of the l-th qualitative level of BGL in a certain time slice are given below:

$$p_{\inf} = \frac{1+d_l}{K+N} \qquad p_{\sup} = \frac{1+d_l+M}{K+N} \qquad (1)$$

where p_{sup} and p_{inf} are the upper and lower bounds, respectively, d_l is the number of days in which the episode corresponding to the l-th level is verified, N is the total number of monitoring days, and M is the total number of missing data. It is worthwhile noticing that the upper and lower probability bounds coincide when N=0, and are equal to 1/5, corresponding to a uniform probability distribution over the 5 levels.

Problems are identified when $p_{inf} > \alpha$ and $p_{sup} < \beta$, being α and β two parameters that by default are equal to 0.3 and 0.8 respectively, when RBR is applied with no integration. Through the Case Based retrieval tool, the problem identification task can be specialised, by setting the two parameters to more proper values, depending on the case features. In more detail, Case Based retrieval is implemented as a two-step procedure: a classification step, and an actual retrieval step. In the problem identification task, only classification is exploited. The input case is classified relying on a taxonomy of prototypical classes, that describe the most common situations a paediatric diabetic patient may incur in (see figure 1). α and β assume the values associated to the most probable class for the case at hand, identified by resorting to a Naive Bayes technique [4], that makes the hypothesis of conditional independence among the features given a certain class. Although this approach makes such a strong assumption, it is known to be quite robust in a variety of situations [5]. Prior probabilities have been derived through the collaboration with the diabetologists of the Paediatric 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 [4].

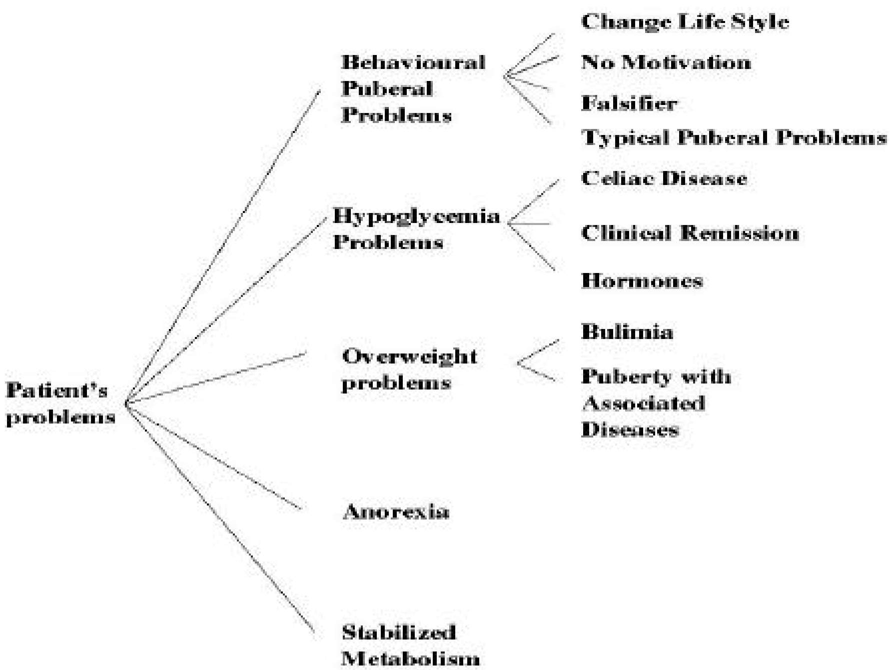

Figure 1: the taxonomy of prototypical situations that may occur to paediatric diabetic patients

2.2 Suggestion generation and selection

A number of rules is applied to propose solutions to the problems derived in task 1. Among all the alternative suggestions generated, only the most suitable are selected. Suggestion selection consists in identifying the most effective ones, and in adapting them to the patient's lifestyle. Insulin modification suggestions effectiveness is calculated relying on the concept of Insulin Activity; the effectiveness at time t of an insulin dose given at time 0 is:

S=IA(t)

where IA(t) is the residual Insulin Activity at time t obtained as in figure 2. The IA is calculated using the model proposed by Hovorka [6] and depends only on the specific insulin type chosen for the patient at hand.
The suggestion generation and selection reasoning task is completely performed by the RBR tool (see [7] for further details).

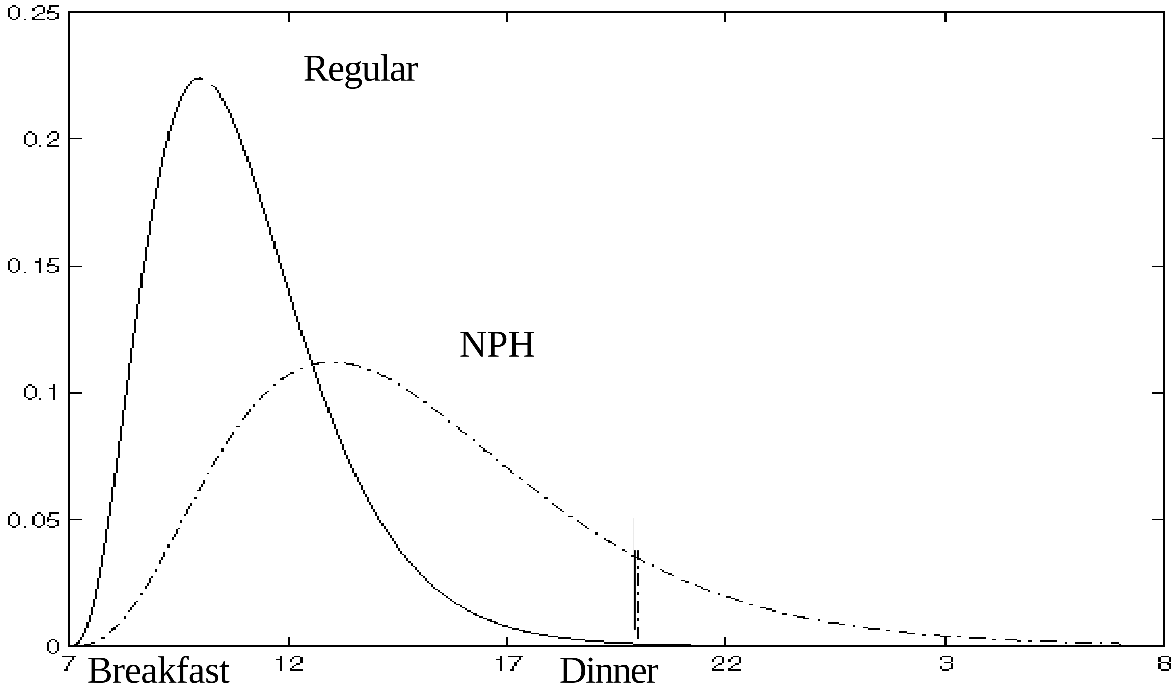

Figure 2: Comparing Insulin Activities for two insulin types: Regular (fast acting) and NPH (slower acting) insulin. For a problem at dinner, a suggestion proposing an adjustment of NPH insulin at breakfast is more effective than one dealing with Regular insulin, injected at the same time slice.

2.3 Application of the selected suggestions to the current insulin protocol

The RBR system typically suggests default solutions that consists in small variations of the current protocol insulin doses, as it is meant to be conservative enough to be safely applicable in a variety of different situations. However, when possible, a model is used to calculate the optimal insulin doses related to the daily schedule obtained by applying the suggestions derived during reasoning task 2. To this end, we have exploited the stochastic version of the model proposed in [8]. This model assumes that a patient reaches a daily cyclo-stationary behaviour in response to a certain insulin protocol. The change in the steady state BGL values is described by a differential equation, that has the following solution:

$$\mathrm{BGL}(t_i,\mathrm{R}_2)=-\mathrm{S/K}\int_{t_i+24}^{t_i}\{[1-r(t)]Iarel(t)[\exp(-K(t_i-t))]\}\,dt+\mathrm{BGL}(t_i,\mathrm{R}_1) \qquad (2)$$

where BGL(ti,Rj,j=1,2) is the steady state value of BGL at day time i, in response to insulin therapy R_1 or R_2, Iarel is the change of the daily insulin activity profile moving from insulin therapy R_1 to R_2, r(t) is a function that expresses the different insulin resistance that may occur during each day, and K and S are the patient specific model parameters. One problem of this model is the need to extract a point estimate that describes the daily behaviour of a diabetic patient. This means to obtain a single daily profile as a summary of the patient's response to a certain therapy (i.e. the modal day). For this reason, the estimate of the BGL modal day has been carried out by resorting to the probabilistic approach described in the previous section. At each measurement time the probability distribution of BGL, discretised in the five qualitative levels already presented, is calculated according to formulas (1). Such distribution is then propagated by resorting to the model (2). The overall procedure results in the Markov model described in figure 3.

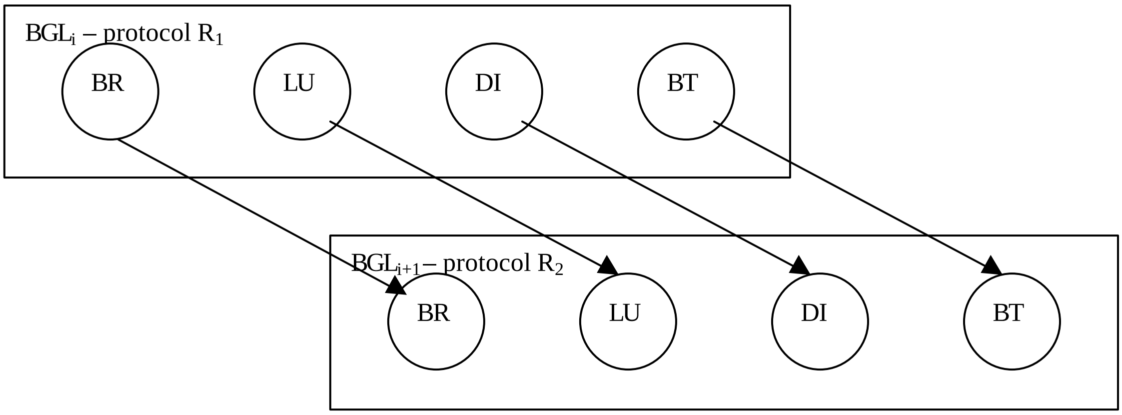

Figure 3: The Markov model describing the propagation of the BGL probability distributions

Rather interestingly, this model has a deterministic transition matrix (given by the model) and a stochastic representation of the BGL state.
The performance of a certain insulin regimen can be therefore measured by calculating its expected utility:

$$EU = \sum_{timeslices} \sum_{k=1...5} BGL_k * C_k \qquad (3)$$

where C_k is a suitable cost associated to each BGL qualitative level. Figure 4 shows the cost function C in dependence on the BGL values.
This scoring function allows to determine the best insulin protocol modification, according to the decision theory. The expected utility function is maximum for normoglycemia and minimum for hypos and hypers; the doses that maximise it are chosen.
Unfortunately, not always the model turns out to give reliable predictions. This problem may be easily detected during the model parameters identification. When this situation holds, the MMR system performs the CBR retrieval step, restricted to the most probable classes identified during reasoning task 1. In more detail, the physician is allowed to choose whether to retrieve only cases belonging to the most probable class, or to a set of very probable classes. In both situations, cases are retrieved by resorting to metrics able to cope with the problem of missing data, and to treat both symbolic and numeric variables [9]. When dealing with a very large case library, it is possible to perform a non exhaustive search procedure, exploiting a pivoting algorithm [10], that greatly reduces the retrieval time [4]. Some simple statistics are calculated on the retrieved cases, to set the insulin

adjustments width that will then be applied to the current protocol. Therefore, MBR and Case Based retrieval are used in a mutual exclusive way to specialise the rules behaviour.

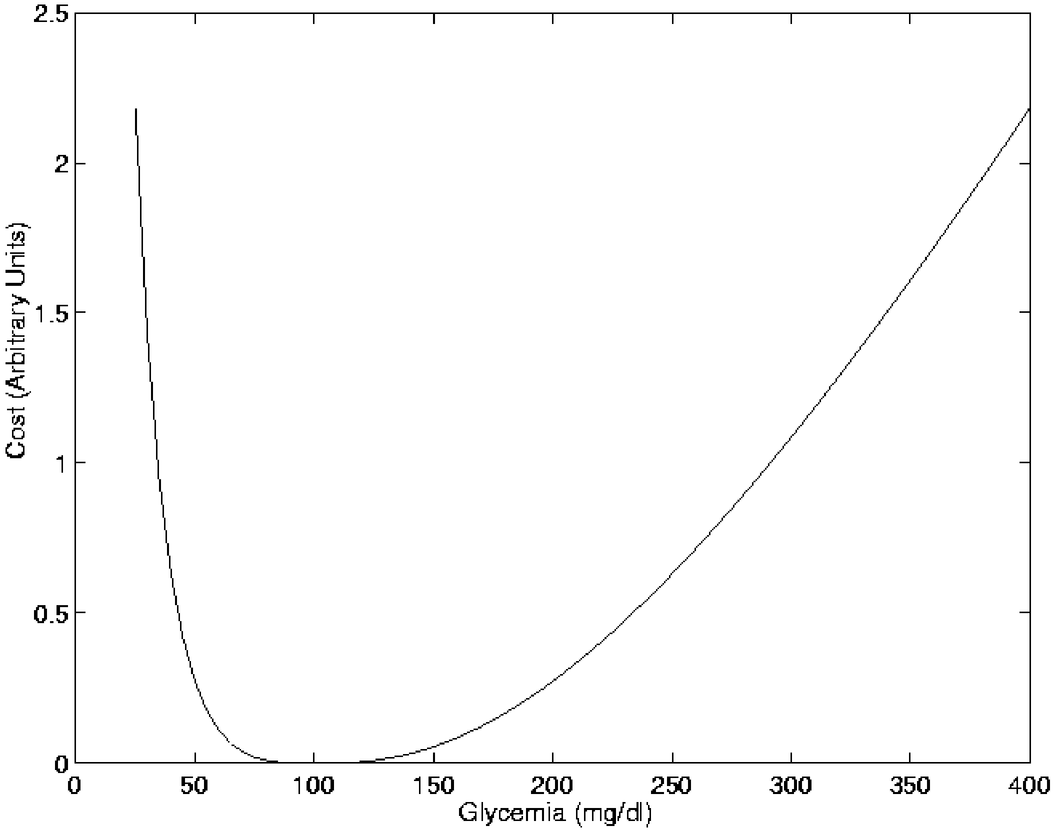

Figure 4: The cost function C in dependence on the BGL values

2.4 Selection of additional library protocols

After having adapted the current therapeutic protocol to the problem at hand, similar protocols can be retrieved from a library of past protocols. The final choice is then left to the physician, who is also allowed to edit a different therapy, if she/he believes that the proposed ones are unreliable.

3. First evaluation results

A first evaluation procedure of the MMR methodology described in this paper was carried out resorting to a real patients' data set, provided by the Paediatric Department at Policlinico S. Matteo.

The results may be summarised as follows:

1. it is usually possible to obtain a model that leads to reliable predictions when dealing with "simple" situations (i.e. cases in which the correct therapeutic strategy can be easily identified). Obviously, when the model can be exploited, it provides the optimal insulin doses adjustments. In particular, "simple" situations correspond to all situations in which a clear causal effect of insulin dosages on the BGL can be detected in the data.
2. on more complex situations (such as "brittle control" or "Somogyi effects" [11]), the model cannot be effectively used; in these examples, the possibility of exploiting past cases similar to the current one, retrieved through the CBR methodology, is very

helpful for the definition of a proper therapy. In comparison to the application of RBR with no integration, the exploitation of retrieval results leads to a sharper and more suitable insulin doses adjustment, customised for the patient at hand;

3. on the other hand, when the case library content is poor, the retrieval results may lead to an unfit rule specialisation. In this condition, only RBR can provide a reliable (even if maybe too conservative) solution. Nevertheless, the CBR methodology enables an easy knowledge storing and upgrading. The overall system will automatically improve its competence during routine clinical practice, as new cases will be stored in the HIS without requiring an additional work load to physicians, and will contribute to reduce the competence gaps. Through the memorisation of new information, the system is therefore able to learn how to cope with more and more complex situations.

4. Conclusions

We have presented a MMR system that integrates RBR, CBR and MBR, with the aim of supporting patients management and therapy revision in the IDDM domain. This MMR methodology can also be seen in a KM perspective, as a valuable instrument for knowledge sharing, distributing and reusing. As a matter of fact, through case classification and retrieval, the tool is able to contextualise and categorise cases, transferring the implicit knowledge into an explicit form, and making it immediately exploitable by the physician. When successful, model identification enables to extract from the data the available information, by exploiting the explicit knowledge contained in the model itself.

Moreover, defining a new therapy scheme for the situation at hand, as it would happen without the use of the MMR system, would be an activity of implicit knowledge creation: the new information would be just stored in the HIS, in a form not ready for reuse. The MMR methodology, instead, enables the physician comparing her/his own decision with the therapy automatically suggested: this decision assessment procedure transforms the new therapy into explicit knowledge, already analysed in the light of both formalised information (due to the model and to the RBR component application) and past experience (due this time to model identification and to the CBR component exploitation).

Acknowledgements

Marinella My is gratefully acknowledged her help in implementing the model. We also thank Dr. Giuseppe d'Annunzio for having provided us with the patients' data, and for his cooperation in formalising the medical knowledge.

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Some methodological Issues concerning Computer Supported Case Based Reasoning in Medicine

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Abstract. Some methodological aspects of the process of the integration of Biomedical Technology, Information Technology, and Medical Decision Making that result in Computer Supported Case Based Reasoning in Medicine are examined.

1. Introduction

The purpose of this paper is to deal with some methodological aspects of the process of the integration of Biomedical Technology, Information Technology and Medical Decision Making, that result in Computer Supported Case Based Reasoning in Medicine. The multi-faceted character of the human organism has always led physicians to employ a casuistic approach to clinical practice. Attempting a generalization of the experience accumulated during related recent research and development activities, some important aspects of this agendum will be presented, concerning Medical Inference and Case Based Reasoning, examining the employment of electronic Patient Records, in various Decision Supporting Systems, and touching questions regarding Case Based Reasoning, as an important medium to promote Interdisciplinary Medical Education.

2. Some Historical Remarks on the Development of Medical Reasoning

The concepts, the classificatory schemata and the methods involved in diagnosis and treatment are subject to the prevalent at the time theoretical model of disease. Pre-Hippocratic medicine had a religious, a magical and even a mystical character. Hippocratic medicine changed the approach to illness. Diseases were explained in terms of intra-corporeal causes, and consequently, treatment was the reestablishment of the proper balance. The Galenic system introduced a symptoms-based diagnosis and a general principle of treatment , the contraria contrariis curantur (cure by contraries), which, led to the stagnation of medicine by becoming a dogma. The introduction of the notion of the necessity of experimentation in medicine by the Arabs and especially by Ibn Sina (Avicenna) was the only noteworthy development in the fifteen centuries of Hippocratic-Galenic dominance of the field.

The development of medical practice from Paracelsus to the middle of the nineteenth century, comprises of, first, the attempt to formulate a taxonomy and a strict aetiology of diseases, second, the placement of bodily phenomena exclusively in the realm of natural phenomena, third, the systematic examination of the structure and the function of the body and its organs, and finally, the impact of the natural sciences such as physics, chemistry and biology on medical practice [1].

Two events may be considered as marking the birth of contemporary biomedical technology. The first was the discovery of x-rays by Roentgen in 1895, an event which fulfilled the wish of all physicians since antiquity to "see" the inside of the human body. Roentgen's discovery allowed the non-invasive imaging of the human body and thus induced a revolution in medical practice. Einthoven, on the other hand, in 1901, measured for the first time the bio-electrical potentials (ECG) of the heart's action, on the body, contributing thus to the rejection of views associated with the notion of vis vitalis. These two events led to a close collaboration of physicists and physicians which resulted in the development of a methodology common to both the natural science and to medicine which, in turn, led to an impressive growth of biomedical technology.

Contemporary diagnostic procedures entail the use of biomedical technology and are intimately related to its development. These procedures consist of the collection of diagnostic information and the evaluation and assessment of the individual patient. The evaluation of the data collected and the individual assessment of the patient depend on the theoretical models of disease adopted at the time, and on the difficulty of establishing criteria of normality and abnormality in human biology.

3. Medical Inference and Case Based Reasoning.

Every activity entails decision making. Decisions are the basic components of scientific, professional and private life, and Medical Reasoning [4],[5] constitutes the essence of Differential Diagnosis, which actually forms the “hard core” of Medical Sciences. The typical methodological approach to obtain a diagnostic conclusion, is the comparison of the “*data*”-set collected from the patient with a similar *"reference"*-set of data, which represents the *"normal"* condition and which is defined in a more or less arbitrary manner being based on previous, collective experience. The difference of the sets constitutes the *"symptoms"*-set, which is intended to lead to the successful diagnosis. An implicit assumption in the above procedure is that a pathogenetic process leads to a *"nosos"* [disease]. This disease is manifested through an alteration of morphological and functional features, which are exhibited as parameters, detected (or are expected to be detected) through the clinical information, the in vivo signals, the in vitro values and the medical images obtained during the diagnostic procedure.

It is further assumed, that there is a well defined variation range of the above mentioned data, which is empirically known to correspond to a *"normal"* status of the human individual (health-state) and that the data exceeding this variation interval, indicate the appearance of an *"abnormal"* status of the individual (disease state). An additional implicit assumption made is that the detection of an adequately large set of disturbed data ("symptoms"- set) allows for to conclude that a certain disease is present which is induced by the same pathogenetic factors such as have been observed to result in the same or similar disturbance (symptoms) in a "reference" case. These assumptions are not always valid and it is often very difficult or even impossible to satisfy them mainly be cause of the huge number of parameters influencing the health condition of a certain individual and the criteria by which the elements of the corresponding sets are selected.

However, the diagnostic procedure might be successfully completed because the lack of information is substituted by a "diagnostic feeling", developed by the physician and which is based on the length of his practice and a belief in the uniformity and regularity of phenomena. The step from diagnosis to treatment is based on the expectation that the human body will behave in an identical manner under similar conditions. The above discussion presupposes that there is a certain "property" of some individuals which can be referred to as "medical expertise". This "property" entails, first, medical information which is organized according to some taxonomic schemata. Second, it contains criteria for the logical evaluation of the inferences made and, third, selection rules which allow the appropriate use of the acquired knowledge. Finally, a fundamental component of medical expertise is that which was referred earlier as "diagnostic feeling".

4. Creating computer-supported Case Based Reasoning

The question, at this point, is whether "medical expertise" can be formalized and transferred into an appropriate computer system. This transfer, however, must satisfy certain conditions, the first of which is the formation of a knowledge base which comprises of codified and classified medical information. Further, it should provide a set of algorithms, which allow the formal-mathematical interpretation of the criteria employed in an evaluation, and selection rules, which are applied in medical praxis. Third, it must attempt to incorporate "diagnostic feeling".

There are various sources of medical information which constitute the knowledge base. The cognitive framework of the processing, and the constraints which arise in the context of each given situation, are expressed through the formation of functions and sets, that represent the classified and codified medical knowledge. An additional aspect is the definition of the operations and the operators that lead to the evaluation of the medical information and the implementation of the selection criteria and the decision making rules. Finally, there is the selection of the boundaries that set implicitly the demarcation criteria between "health" and "disease" and which allow for the quantification of the extent of the action to be taken when such an action is deemed necessary.

The various aspects of processing of medical information are structured as reasoning models which enable the apparatus to make inferences and reach conclusions. Such a model can be expressed in a generalized form by a function:

$$F = F\,\{f_1(x_{11}, x_{12}, \ldots x_{1n}),\ f_2(x_{21}, x_{22}, \ldots x_{2n}),\ \ldots\ f_k(x_{m1}, x_{m2}, \ldots x_{mn})\}$$

where, fi and x_{jl} stand for various logical or analytical functions and the corresponding parameters of terms which constitute the individual patient “case”. A the case-based reasoning model, is that, where the function F and its components are compared to a number of cases, which have been already evaluated by experts. The number of such cases, which can be steadily increasing, allows for the selection and definition of a "measure" of comparison between the case at hand and the other cases. On the basis of that "measure", the case which most approximates the case under consideration is selected and constitutes the basis of the diagnosis and treatment proposal :

$$\| F - F_e \| \to 0$$

where e = 1,2,3,...E, and E represents the evaluated and saved cases at the given time. The operator || || is individually defined differently in each case-based reasoning system and sets implicitly the boundaries of its application. Case-based reasoning is possible only insofar, as the experience and the corresponding "diagnostic feeling" of several experts can be incorporated in the system and the cases treated by them can be reproduced.

There are two groups of major difficulties in the application of case-based reasoning systems, in complex medical situations. The first set concerns the difficulties in providing functions and values, because the input data must be available in a standardized form, something which is not always possible, at least today, especially in the case of medical images. In real world applications, we attempt to solve this problem, first, by introducing feasible approximations, thus, reducing the number of the employed parameters, and, second, by employing several data conditioning preliminary stages, which simplify the model, however, they reduce the sensitivity and the overall performance of the model.

The second source of uncertainty, is the required evaluative calculus, in order to assign a relative importance to the items of information, included in the knowledge base, since all the data concerning a case, do not have equal weight in the diagnostic and treatment process decided upon. Numerous powerful methods, such as neural networks, fuzzy sets, statistical techniques etc. [2], [3], [8], [9] combined to signal and image processing algorithms, are presently applied. They primarily attempt to simulate the human diagnostic procedures, by incorporating at least fragments of the interaction between patient and physician, by adopting the public inferential principles employed, and by replicating the private principles of several experts.

The casuistic approach, allows for a flexible approach to diagnosis and emphasizes the individual aspects of treatment. Thus, case-based reasoning systems in medicine, may provide an adequate approximation of the function *F*, which describes the state of the patient. Further, it enables the physician to detect and evaluate the abnormality region in each value domain, provided that the subject-matter of a problem group in a clinical specialty, is thoroughly defined, the knowledge and experience concerning it, is adequately founded, on the basic medical sciences, and, finally, there is plenty of relevant clinical data available.

5. The employment of Medical Records in Computer Supported Reasoning.

Medical records usually include, first, clinical information obtained by the case history, and by the physical examination, second, data acquired through various diagnostic procedures, third, information related to various therapeutic interventions and, lastly, data which are of administrative and of financial importance such as insurance, costs of medical treatment, cost of hospitalization etc. [11].

Medical records are used in a variety of ways and they serve a multiplicity of purposes. The first of these functions, is that of the use of the records in the treatment process. On the basis of information included in the record, the physician reaches a diagnosis and charters the course of the intervention, and, on the basis of the record, a patient is enabled to make informed decisions, concerning the proposed treatment. The second important point is, that the education and the training of physicians, nurses and other health care specialists, necessitates their acquaintance, with data derived from clinical practice, in addition to their formal education and the information they derived from textbooks and other publications. Information registered in patient’s records must be precise and comprehensive, since data concerning clinical trials of novel therapeutic schemata and statistical data involved in epidemiological research, derive from these records.

Knowledge bases, used in various decision supporting systems, are composed by the selective employment of components of the records, and consequently, various research programs and their methods, are bound to the structure, the availability and the handling of the medical records. Most of these data can be found primarily, only in medical records. However, the dissemination of data deriving from medical records in the medical networks, poses the danger of eliminating the individual characteristics of the specific patient, and the only thing which remains in any specific Computer Supported Reasoning application, is an abstract, conceptual and impersonal condition.

6. Medical Education and Case Based Reasoning.

The optimization of the decision making processes in Medicine, requires continuous training. On the job training, contributes to the promotion of interdisciplinary research, by addressing, through specific case handling, in an effective manner, the problem on intra-specialty communication. On the other hand, hypertext and multimedia courseware, are gaining importance in Medical Education [6], [7], [10] and they can be used in order to offer clinical-practice oriented training. Web-based and other emerging technological alternatives promise to reach various groups, offering them continuous education services. These groups may comprise also of those, who are already engaged in professional work, such as physicians, nurses, engineers, physicists, technicians etc.

Case based reasoning systems can play an additional role, in Medical Education, that of contributing to the acquisition and dissipation of clinical expertise since, first, they familiarize the trainee with a rich empirical content, often not available in individual clinics, second, by relating this content to the theoretical aspects of the specific cases, and third, by revealing the " diagnostic feeling" involved in diagnosis and treatment. This supporting role and, especially, the important function, which case based reasoning systems should have in the structure, the methods and the content of medical education, underscore the need of further research in the theoretical aspects and the actual development of such systems

7. Concluding Remarks

Concerning the attempts to improve the diagnostic significance, emerging out of measured biological parameters, related to several bodily functions, we have to point out, that the nature of Medical decision making must be examined presently in order to determine the special characteristics of its components, i.e. the reasons, the method of inference and the ensuing actions.

These reasons refer usually both, to biological functions, and to the aspects which are unique to the problem in question, that is they express the specific parameters which allow for the instantiation of the specific problem. Decision making concerning the real patient, can be assisted by decision supporting systems, relying on case-based reasoning models, like the ones described above.

Finally, pertaining to the development of case based on-line educational means, addressing needs which stem out of the theoretical and practical aspects of medical decision-making, it should be kept in mind, that medical data, disseminated in the Web or available in other digital forms, constitute cost-effective and practical means, augmenting equality in medical training, however, they may result in a new type of *fragmentation* and *compartmentalization* of the patient's body and personality, thus endangering the interpersonal relation between him and the physician, if the social and ethical premises are neglected, in the mode of the presentation of the medical inferences employed.

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