Case-Based Decision Support for Patients with Type 1 Diabetes on Insulin Pump Therapy

Cindy Marling[1], Jay Shubrook[2], and Frank Schwartz[2]

[1] School of Electrical Engineering and Computer Science
Russ College of Engineering and Technology
Ohio University, Athens, Ohio 45701, USA
marling@ohio.edu
[2] Appalachian Rural Health Institute, Diabetes and Endocrine Center
College of Osteopathic Medicine
Ohio University, Athens, Ohio 45701, USA
shubrook@ohio.edu, schwartf@ohio.edu

Abstract. This paper presents a case-based approach to decision support for diabetes management in patients with Type 1 diabetes on insulin pump therapy. To avoid serious disease complications, including heart attack, blindness and stroke, these patients must continuously monitor their blood glucose levels and keep them as close to normal as possible. Achieving and maintaining good blood glucose control is a difficult task for these patients and their health care providers. A prototypical case-based decision support system was built to assist with this task. A clinical research study, involving 20 patients, yielded 50 cases of actual problems in blood glucose control, with their associated therapeutic adjustments and clinical outcomes, for the prototype's case base. The prototype operates by: (1) detecting problems in blood glucose control in large quantities of patient blood glucose and life event data; (2) finding similar past problems in the case base; and (3) offering the associated therapeutic adjustments stored in the case base to the physician as decision support. Results from structured evaluation sessions and a patient feedback survey encourage continued research and work towards a practical tool for diabetes management.

1 Introduction

Not long ago, a waitress we will call Sally collapsed at the restaurant where she was working and was taken, unconscious, to the hospital emergency room. Sally, who has Type 1 diabetes, was in a coma due to severely depressed blood glucose levels, a problem known as hypoglycemia, or insulin reaction. The diabetic coma is a serious condition that can quickly lead to permanent brain damage or death. When efforts to restore Sally's blood glucose levels and revive her were successful, her physician turned his attention to preventing such occurrences in the future.

In Type 1 diabetes, the pancreas fails to produce insulin, an essential hormone required to convert food into energy. Therefore, patients with Type 1 diabetes

K.-D. Althoff et al. (Eds.): ECCBR 2008, LNAI 5239, pp. 325–339, 2008.

must depend on exogenous supplies of insulin to survive. Too little insulin results in elevated blood glucose levels, called hyperglycemia. Hyperglycemia can lead to numerous diabetic complications over time, including blindness, neuropathy and heart failure. Patients who take insulin to avoid hyperglycemia are subject to hypoglycemia, which occurs when they inadvertently take too much insulin. Hypoglycemia may cause weakness, confusion, dizziness, sweating, shaking, and, if not treated promptly, loss of consciousness or seizure. On the surface, the solution to Sally's problem may seem simple: she should take less insulin. Unfortunately, despite the best efforts to precisely balance insulin dosages with physical requirements, managing blood glucose levels is still a difficult and demanding task. It is a task faced by patients with Type 1 diabetes every day, who must keep their blood glucose levels as close to normal as possible, avoiding both hyper and hypoglycemia, to maintain their health and avoid serious disease complications [1].

In Sally's case, there was more to the story than just her physical manifestations. It turns out that Sally collapsed toward the end of her twelve-hour shift working as a waitress. Despite the facts that Sally had been wearing her insulin pump and had taken regular breaks for meals and snacks, the demands of her job created too much physical stress for her body to handle. In addition, from having had diabetes for many years, she no longer sensed the typical symptoms of hypoglycemia experienced by most people with diabetes. This condition, called hypoglycemia unawareness, made her especially vulnerable to hypoglycemia. For financial reasons, Sally needed to work as many hours as possible. Her employer urged her to work part-time, but Sally did not feel she could afford to do that. Her physician (the third author) proposed a compromise, in which she could still work a full forty hour week, but would not work more than eight hours in a single day. This solution worked for Sally, whose life has returned to normal.

Physical, social and lifestyle factors, with their myriad permutations and complex interactions, impact blood glucose levels in patients with Type 1 diabetes. To provide individualized decision support that can help each patient maintain good blood glucose control, we propose a case-based approach. The use of CBR to enhance rule-based and model-based reasoning for diabetes management was first introduced by the T-IDDM project [2]. Our work differs from this project in three important ways: (1) it uses CBR as the primary reasoning modality, rather than as an adjunct to other reasoning approaches; (2) it adds consideration of life event data, which may influence blood glucose fluctuations; and (3) it focuses on patients on insulin pump therapy, a more advanced and flexible treatment regime than that used by T-IDDM patients.

Traditionally, people with Type 1 diabetes recorded their daily blood glucose readings in paper log books. These logs were presented to the physician for review and analysis at office visits three or four times per year. Today, continuous glucose monitors can record blood glucose data every five minutes, and insulin pumps and glucose meters collect and store data daily. Patients can email this data to their physicians every day or every week. Commercially available software can acquire, transfer and plot data, but it does not, at present, provide

data analysis. This leaves physicians with the complex and time-consuming task of interpreting voluminous blood glucose records and making appropriate therapeutic adjustments. Studies have shown that physicians may feel overwhelmed by data overload, which may lead to "clinical inertia," in which physicians do not even try to regularly adjust therapy for diabetes patients during their scheduled office visits [3,4].

Our goal is to ease the physician's task by automatically analyzing patient data and providing therapeutic recommendations comparable to those an endocrinologist or diabetologist would make. Initially, recommendations would be provided to physicians for review. We envision that, once proven safe and effective, decision support software could be embedded in patient medical devices, directly assisting patients with their daily diabetes management.

CBR seems especially appropiate for diabetes management for several reasons. First, the established guidelines for managing diabetes [5] are general in nature and must be customized to meet the needs of each patient. Cases can help to complement and individualize such general guidelines, as noted in [6]. Second, the factors that influence blood glucose control are both quantitative (e.g., blood glucose readings and insulin dosages) and qualitative (e.g., perceived stress and food preferences). CBR systems have long integrated the quantitative with the qualitative for applications ranging from generating expressive music [7] to menu planning [8] to recommender systems [9]. Finally, CBR has been successfully applied to other long-term medical conditions that can not be cured but must nevertheless be managed [10,11,12,13].

This paper presents a case-based approach to decision support for diabetes management in patients with Type 1 diabetes on insulin pump therapy. It describes the construction and evaluation of a research system prototype. It concludes with an overview of related research and plans for future work.

2 System Prototype Construction

2.1 Knowledge Acquisition and Representation

Existing diabetes information systems focus primarily on blood glucose levels and insulin dosages, and sometimes store limited data concerning the times of meals, carbohydrate consumption, and timing of exercise. As knowledge engineers shadowed physicians and conducted structured interviews, it became apparent that endocrinologists and diabetologists consider many more features when determining appropriate therapy for patients with Type 1 diabetes on insulin pump therapy. The most significant factors involved are shown in Figure 1.

Because these features are not routinely maintained, in either electronic or non-electronic form, it was not possible to build cases for the case base from existing patient records. Therefore, a preliminary clinical study involving 20 patients with Type 1 diabetes on insulin pump therapy was conducted to acquire cases for the system. A 44-table Oracle database with a Web-based user interface was designed and implemented to store the data provided by the patients participating in the study. Each patient submitted extensive daily logs documenting

Problem Description Features
High and Low Blood Glucose Target Levels
Actual Blood Glucose Levels throughout the Day
Insulin Sensitivity (patient specific reaction to insulin)
Carbohydrate Ratios (patient specific need for insulin with food)
Type of Insulin Used
Basal Rates of Insulin Infusion throughout the Day
Bolus Doses of Insulin with Food Consumption
Bolus Doses of Insulin Used to Correct for Hyperglycemia
Type of Bolus Wave for Each Bolus
Actions Taken to Self-Correct for Hypoglycemia
Meal Times
Amount of Carbohydrate Consumed at Each Meal
Specific Foods Consumed at Each Meal
Alcohol Consumption
Mechanical Problems with the Insulin Pump
Time of Change of Insulin Infusion Set
Location of Insulin Infusion Set on Patient's Body
Time, Type and Duration of Exercise
Work Schedule
Sleep Cycles
Menstrual Cycles
Stress (as subjectively determined by patient)
Illness (other than diabetes, such as cold or flu)

Fig. 1. Significant Features Used by Physicians to Determine Appropriate Therapeutic Adjustments for Patients with Type 1 Diabetes on Insulin Pump Therapy

their daily values for the features shown in Figure 1 over a six-week period. Once collected and reviewed by physicians, this data was used to structure cases. Each case represents one problem in blood glucose control for a specific patient, along with its associated physician-recommended solution and clinical outcome.

Patients participated in the preliminary study between February, 2006 and June, 2007. From one to four patients participated at a time. The number of patients who could supply data at once was limited by the available resources, including continuous glucose monitoring devices and physician time. Throughout the length of the study, knowledge engineers met with physicians weekly to review the patient data collected for that week. The immediate goal of each weekly meeting was for the physicians to examine the data, find problems in blood glucose control, and suggest therapeutic adjustments to help patients correct or prevent these problems. To facilitate this data review process, knowledge engineers provided the physicians with written data summary reports for each patient. They also built a data visualization tool to display all of the different types of data available for a patient over a 24-hour period.

Following each weekly meeting, physicians would contact patients to recommend therapeutic adjustments for the problems discovered in the data. In subsequent weeks, the data was monitored to evaluate the clinical outcome of each adjustment. A recommended adjustment might resolve a patient's problem, provide some degree of benefit but not completely resolve a problem, or fail to resolve a problem. Follow-up also ascertained if the patient had accepted and applied the recommended adjustment or not. Knowledge engineers then structured the problems, solutions (adjustments) and outcomes into cases for the case base. A total of 50 cases were built for the system prototype during the study.

2.2 Example Case: Problem of Nocturnal Hypoglycemia

The problem of nocturnal hypoglycemia was found in a 56-year-old female patient who had had Type 1 diabetes for 32 years. This patient had been on insulin pump therapy for eight years, and was generally well controlled, as evidenced by her HbA1c tests, which measure long-term blood glucose control. When her first week's data was displayed to her physician, as shown in Figure 2, it was evident that she had been hypoglycemic all night long without sensing it. This

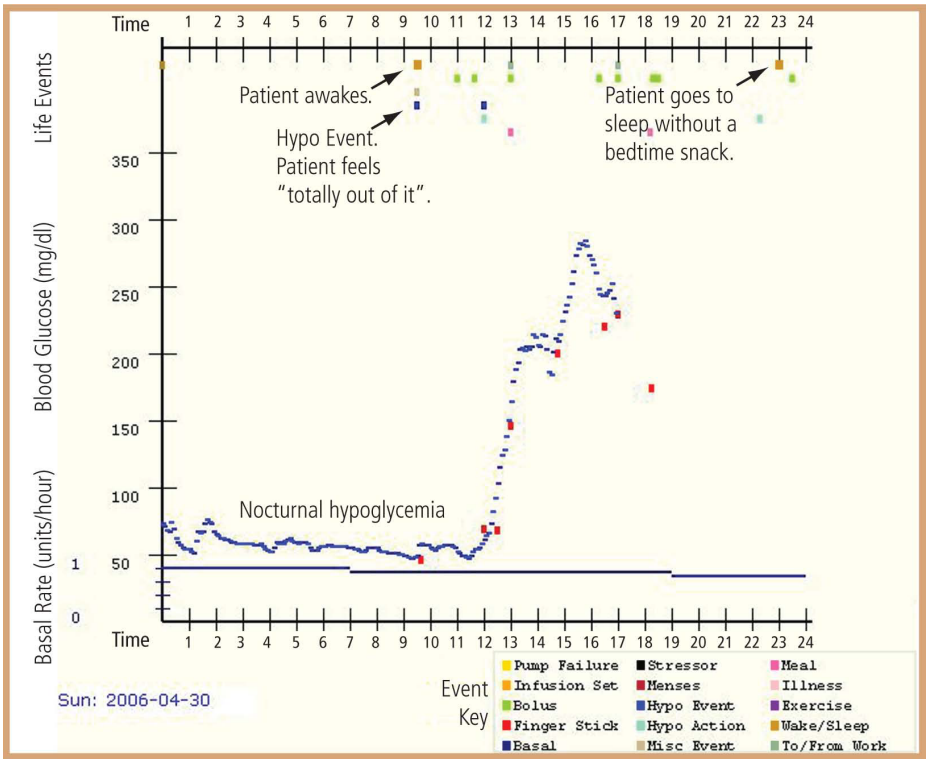

Fig. 2. Data Visualization Display for Patient with Nocturnal Hypoglycemia

is a serious problem, because untreated hypoglycemia can lead to diabetic coma and/or death.

In the data visualization display of Figure 2, blood glucose levels are indicated on the vertical axis, while time, beginning at midnight, is indicated by the horizontal axis. A curve, displayed in dark blue, shows the data captured by the continuous glucose monitoring device, while individual red dots show blood glucose values obtained through routine finger sticks. Life events recorded by the patient are denoted by markers at the top of the display. These are arranged by time of occurance, so that daily activities that impact blood glucose levels can be viewed together with the blood glucose values themselves. Clicking on a life event marker displays additional information as recorded by the patient.

In Figure 2, the patient's problem with nocturnal hypoglycemia is evidenced by the continuous glucose monitoring data curve between midnight and 9:30 AM. When she awakes at 9:30 AM, she takes a finger stick measurement, and reports that her blood glucose level is 46 mg/dl, which is dangerously low. She also reports that she feels "totally out of it" and is unable to take action to correct her hypoglycemia. The physician examined the rest of the data displayed to determine what might be causing this problem and what could be done to

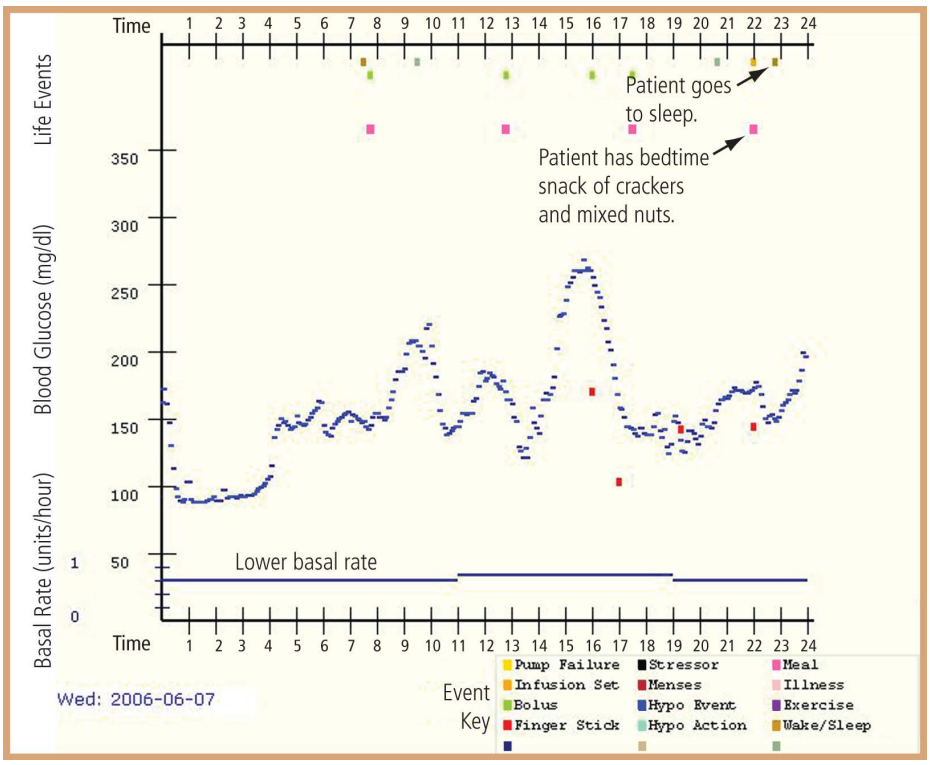

Fig. 3. Data Visualization Display of Successful Resolution of Nocturnal Hypoglycemia

eliminate it. By checking the meal markers at the top of the display, he could see that the patient was not eating snacks before bed. He recommended that she always eat a bedtime snack, and also that she lower her rate of basal insulin infusion by 0.1 units per hour between midnight and 7:00 AM. The basal rate is shown by the line at the very bottom of the display. The physician's recommended solution included adjustments to both diet and insulin intake. Having more food in a patient's system overnight helps to prevent blood glucose levels from falling. Because insulin depresses blood glucose levels even further, the basal rate of insulin infusion was decreased overnight.

In Figure 3, data for the same patient is displayed toward the end of her participation in the study. It is clear that she has taken the physician's advice, as her basal rate now appears lower and a meal marker indicates that she has eaten a bedtime snack. It is also clear from the blood glucose data displayed that the patient is no longer hypoglycemic overnight. This solution was therefore deemed to have a successful outcome.

This problem, solution and outcome comprise one of the 50 cases in the case base. Should another patient experience nocturnal hypoglycemia, this case may be recalled to suggest applicable therapeutic adjustments. A more detailed description of the abstract case representation is presented in [14]. Three cases are presented from a physician's perspective in [15]. Internally, a case is represented as an object of a hierarchical Java class containing over 140 data fields.

2.3 Reasoning with Cases

A prototypical case-based decision support system was built with the case base described above as its central knowledge repository. The system operates as shown in Figure 4. The patient enters daily blood gluose and life event data into the database via any available Web browser. Situation assessment software then searches the database to find problems in blood glucose control. Twelve different types of problems, defined during the preliminary study, can be detected. These problem types are listed in Figure 5. Next, the specific problems detected for the patient are displayed to the physician, who must select a problem of interest. The selected problem, with its associated values for all relevant features, becomes the input to the case retrieval module.

Cases are retrieved using a traditional two-step process in which: (a) a subset of potentially similar cases is identified; and (b) the most usefully similar cases are selected from that subset. The initial partition of the case base is based solely on problem type, as shown in Figure 5. For example, if a patient experiences hyperglycemia upon awakening, then other problems of this type or closely related types may be relevant. However, cases involving problems with hypoglycemia would not be useful or relevant, even if they share surface features like time of day or pattern of occurance.

To select the most usefully similar cases from the initial subset of potentially relevant cases, a standard nearest neighbor metric is used. Domain specific similarity functions compute the degree of correspondence between the input case and each potentially relevant case on 18 distinct problem features. An aggregate

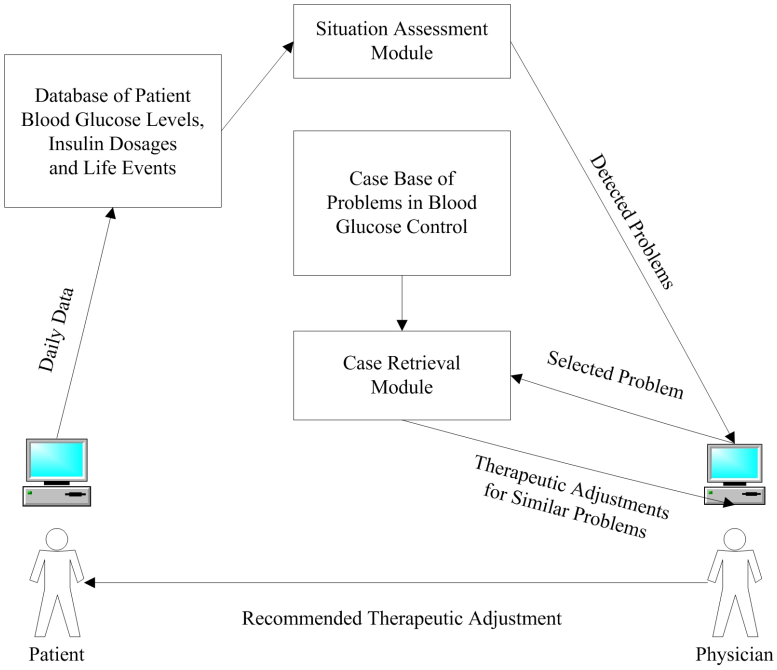

Fig. 4. Overview of Prototypical Decision Support System Operation

match score is then computed for each case by weighting the relative contribution of each feature toward the match. Next, the highest aggregate score is compared to a numeric threshold to determine if the best matching case is similar enough to the input case to contain a therapeutic adjustment of potential benefit. If so, the best matching case is displayed to the physician. Because similar problems often have similar solutions, the best matching case may aid the physician in determining an appropriate therapeutic adjustment for the current patient. It is up to the physician to determine whether or not, and in what form, to relay the retrieved solution to the patient.

The best matching case for the problem presented in Section 2.2 was recorded for an 18-year-old male patient. This patient reported waking up in a sweat at 2:00 AM with a blood glucose level of 49 mg/dl. In the first step of the retrieval process, this case is selected as potentially relevant, because both problems involve hypoglycemia. In the second step, the two cases are found to be similar in many respects, including time of day and relationships to meals, boluses, exercise and stress. They differ in the methods by which the problems were detected and also in the frequency with which the problems occurred. The physician's advice to the patient in the best matching case was, "The patient should have at least a small bedtime snack, perhaps a glass of milk." This solution overlaps with, although it is not identical to, the solution recommended for the patient in the input case.

1. Hyperglycemia upon wakening
2. Hypoglycemia upon wakening
3. Over-correction for hyperglycemia
4. Over-correction for hypoglycemia
5. Over-boluses for meals
6. Pre-waking hypoglycemia
7. Post-exercise hypoglycemia
8. Pre-meal hyperglycemia
9. Pre-meal hypoglycemia
10. Post-meal hyperglycemia
11. Post-meal hypoglycemia
12. Possible pump or infusion set malfunction

Fig. 5. Blood Glucose Control Problem Types Detected During Situation Assessment

3 Evaluation and Feedback

A patient exit survey and two structured feedback sessions for diabetes practitioners were administered to evaluate the feasibility of case-based decision support for patients with Type 1 diabetes on insulin pump therapy. The exit survey questioned patients about time requirements, ease of use, and benefits of participating in the study. Patients did not evaluate actual outputs from the prototype, as it was built after patients concluded their participation in the study. Diabetes practitioners evaluated the outputs from the situation assessment and case retrieval modules of the prototype.

Twelve patients completed the exit survey. Patients reported that the time required for data entry ranged from 15 minutes or less (5 patients) to between 30 and 60 minutes per day (7 patients). While 10 of 12 patients found the Web-based data entry system easy to use, 8 of 12 indicated a preference for having data entry capabilities available on their own insulin pumps or glucose meters. Ten of 12 patients indicated that their increased contact with health care professionals throughout the study was beneficial for their diabetes management. All patients confirmed that it would be beneficial to receive immediate feedback and therapeutic advice from an automated system. When asked, "How likely are you to adopt a therapy adjustment recommended by your doctor?" 10 patients marked *very likely* and 2 marked *fairly likely*. The exact same response was given to the question, "If a computerized therapy adjustment wizard were to recommend a therapy adjustment, how likely would you be to adopt it?" This patient acceptance of the concept of automated decision support suggests that further research could lead to a practical tool for patients, especially if the data entry burden were reduced.

To evaluate the situation assessment capabilities of the prototype, the situation assessment module was run retroactively on the completed patient database. A total of 352 problems in blood glucose control were detected for the patients who completed the study. Ten problem detections were randomly selected for re-

view by a panel of three physicians and one advance practice nurse specializing in diabetes. Each problem detected was shown to the evaluators via the graphic visualization display. Evaluators were then asked to indicate their agreement with each of the following statements:

1. This is a correct identification of a problem
2. It would be useful to call this problem to the attention of the patient
3. It would be useful to call this problem to the attention of the physician

Evaluators agreed with the first statement 77.5% of the time, reported mixed feelings 15% of the time, and disagreed 7.5% of the time. Evaluators agreed with the second statement 87.5% of the time, had mixed feelings 10% of the time, and disagreed 2.5% of the time. Evaluators agreed with the third 90% of the time, reported mixed feelings 7.5% of the time, and disagreed 2.5% of the time.

Leave one out testing was performed to evaluate the case retrieval module of the prototype. During testing, thresholding was turned off, so that the closest match to an input case was always returned, whether or not there was a usefully similar case in the base base. Ten of the 50 cases in the case base were randomly selected as test cases for review by a panel of three physicians specializing in diabetes. For each test case, physicians were given the problem descriptions and recommended solutions of the case and its nearest neighbor. Then they were asked to answer the following multiple choice questions:

1. The problem in the original case and the problem in the matching case are:
   (a) Very Similar
   (b) Somewhat Similar
   (c) Somewhat Dissimilar
   (d) Very Dissimilar
2. Applying the matching case's solution to the original problem would be:
   (a) Very Beneficial
   (b) Somewhat Beneficial
   (c) Neither Beneficial nor Detrimental
   (d) Somewhat Detrimental
   (e) Very Detrimental

Evaluators judged matching cases to be similar 80% of the time and dissimilar 20% of the time. They judged retrieved solutions to be beneficial 70% of the time, neither beneficial nor detrimental 23% of the time, and detrimental 7% of the time. Because not every case in the case base had a usefully similar nearest neighbor, this performance is expected to improve as the case base grows in size.

4 Future Work

A second clinical research study has been designed and approved by Ohio University's Institutional Review Board (IRB). Twenty-eight patients with Type 1 diabetes on insulin pump therapy will participate for three months each. The

first goal of this study is to significantly grow the case base as a central knowledge repository, thereby increasing system competence.

The second goal is to develop patient specific case bases to remember recurrent problems with glucose control and the specific therapeutic solutions that are effective or ineffective for each patient. Each individualized case base will extend the general case base with cases documenting the individual patient's own problems, therapy adjustments and responses. This will enable the system to learn how an individual patient responds to changes in therapy so that the most effective therapy for a particular problem experienced by a specific patient can be recalled. The case retrieval metric will be extended to look first for similar problems experienced by the same patient and to search the central case base only when this does not yield an applicable solution.

The final goal of this clinical research study is to develop new similarity metrics to compare patients with Type 1 diabetes to each other. Then solutions known to work for similar problems in similar patients could be recommended. This is important, because even when problems are similar, lifestyle variations may preclude the successful transfer of therapeutic adjustments. For example, a retiree living alone might be willing to perform therapeutic actions that a teenager would not willingly perform in front of peers at school.

Longer term, we envision extending our work to patients with different types of diabetes, patients on different types of insulin or oral therapy, and patients with special needs, like elite athletes, pregnant women, and teenagers. We hope that eventually, following additional research, development, and safety testing, the software might be directly accessed by patients for continuous blood glucose monitoring and daily decision making support. We maintain contact with the manufacturers of diabetic equipment and supplies to ensure the future viability of our system for patients in the real world.

5 Related Research

The Telematic Management of Insulin-Dependent Diabetes Mellitus (T-IDDM) project was first to explore CBR for diabetes management [2,16,17]. The goals of T-IDDM were to: (a) support physicians in providing appropriate treatment for maintaining blood glucose control; (b) provide remote patients with telemonitoring and tele-consultation services; (c) provide cost-effective monitoring of large numbers of patients; (d) support patient education; and (e) allow insulin therapy customization [2]. T-IDDM integrated CBR with rule-based reasoning and a probabilistic model of the effects of insulin on blood glucose over time. The role of CBR in T-IDDM was to specialize the behavior of rules, by tuning rule parameters, when rules could not provide optimal advice for patients. Cases were found to be especially helpful in providing advice for poorly controlled patients.

Our work shares T-IDDM's goal of supporting physicians in providing appropriate treatment for maintaining blood glucose control, but we have taken a different approach. This may be due, in part, to the differences between treating patients on conventional intensive insulin therapy and on insulin pump therapy.

The therapy regimen for a patient in the T-IDDM project consisted of from three to four insulin injections per day. Each patient had an insulin protocol in which he or she injected the same amount of insulin at the same time of day for each daily injection. The patient then attempted to regulate his or her daily food intake and activities in accordance with this insulin protocol, rather than adjusting the insulin intake to account for variations in daily routine. The data input to the probabilistic model for a patient was the insulin protocol plus three to four blood glucose measurements per day. A therapy adjustment consisted of changing the amount of insulin regularly taken for a daily injection. The model used by T-IDDM was a steady state model that did not account for daily variations in diet or lifestyle, but treated them as stochastic occurrences, or noise. This approach makes sense for conventional intensive insulin therapy, where available data and treatment options are limited. We expect CBR to provide even greater benefits to patients on insulin pump therapy, who can adjust a wider range of insulin and lifestyle parameters to manage their diabetes.

Telemedicine, which aims to enable remote access heath care, has been leveraged in T-IDDM and other research projects that aim to help patients manage their diabetes. Notable examples include VIE-DIAB [18], DIABTel [19], and the Intelligent Control Assistant for Diabetes (INCA) [20]. Telemedicine systems use mobile phones, email, and online applications to enhance data transfer and communication between patients and physicians. When human physicians are the primary sources of knowledge, AI decision support capabilities may be limited or non-existent. The problem with telemedicine approaches that incorporate limited, or no, intelligent decision support is that they can actually *increase* the workload on physicians. This effect was reported in [18], and also documented in a controlled trial of the fiscal and administrative aspects of telemedicine for patients with diabetes [21]. Certainly, the increased availability of patient data without automated data analysis capabilities created the physician overload that motivated our own work.

The dream of an artificial pancreas, which could someday supplant the diabetic patient's own deficient pancreatic function, has led to much work in developing formal models that depend on the relationship between blood glucose and insulin. These models may or may not include the effects of diet, but do not normally include other lifestyle factors, as these could not be automatically detected by an implanted device. The best known model, because of its ready availability for research and educational purposes via the Internet, is AIDA [22]. A number of researchers have tried integrating this model with other decision support techniques, including rule-based reasoning and neural networks [23]. Clearly, efforts to develop an accurate formal model complement efforts to develop intelligent decision support. However, a restricted focus on blood glucose/insulin models that can be embedded in an artificial pancreas presents at least two difficulties. First, the underlying physiological pharmacokinetic relationship is highly complex. Extensive modeling research dates back to the 1960s without the advent of a definitive model [24]. Second, should technical obstacles be surmounted, there will still be financial barriers to providing major surgery for the nearly five

million patients who have Type 1 diabetes worldwide. Case-based decision support may provide a lower cost practical tool in the near-term, as well as account for observed individual variations not currently accounted for by formal models.

Finally, this research builds upon the work of CBR researchers in other medical domains. Workshops on CBR in the Health Sciences have been held for the past five years at the International and European Conferences on Case-Based Reasoning. Overviews of medical CBR have been published in [6,25,26,27]. Among the most closely related projects are MNAOMIA, in the domain of psychiatric eating disorders [10], CARE-PARTNER, for stem cell transplantation follow-up care [11], RHENE, in the domain of end-stage renal disease [12], and the Auguste Project, for the management of Alzheimer's Disease [13]. These research projects, like ours, aim to assist in managing long-term, or chronic, medical conditions. Special challenges in such domains include: (a) handling data that varies over time; (b) accounting for individual variation among patients; and (c) tailoring general guidelines to the needs of individual patients.

6 Summary and Conclusion

This paper has presented a case-based approach to decision support for diabetes management in patients with Type 1 diabetes on insulin pump therapy. A preliminary clinical research study, involving 20 patients with Type 1 diabetes on insulin pump therapy, was conducted. Through this study, 50 cases of problems in blood glucose control, with their associated therapeutic adjustments and clinical outcomes, were compiled in a case base. This case base became the central knowledge repository for a prototypical case-based decision support system. The prototype contains a Situation Assessment module that detects common problems in blood glucose control in large volumes of blood glucose and life event data. It contains a Case Retrieval module that finds the cases containing the most similar past problems in the case base. It displays the therapeutic adjustments from the best matching cases to the physician as decision support in therapy planning. The prototype was evaluated by means of a patient exit survey and two structured feedback sessions for diabetes practitioners. Preliminary results encourage continued research and work toward a practical tool for patients and their health care providers. The case-based approach presented herein has applicability to the management of all forms of diabetes and potential applicability to the management of other chronic medical conditions.

Acknowledgments

The authors gratefully acknowledge support from Medtronic MiniMed, Ohio University's Russ College Biomedical Engineering Fund, and the Ohio University Osteopathic College of Medicine Research and Scholarly Affairs Committee. We would also like to thank Eric Flowers, Thomas Jones, Tony Maimone, Wes Miller and Don Walker for their software development and knowledge engineering contributions.

References

1. The effect of intensive treatment of diabetes on the development and progression of long-term complications in insulin-dependent diabetes mellitus. New England Journal of Medicine 329, 977–986 (1993)
2. Bellazzi, R., Larizza, C., Montani, S., Riva, A., Stefanelli, M., d'Annunzio, G., Lorini, R., Gómez, E.J., Hernando, E., Brugués, E., Cermeno, J., Corcoy, R., de Leiva, A., Cobelli, C., Nucci, G., Prato, S.D., Maran, A., Kilkki, E., Tuominen, J.: A telemedicine support for diabetes management: The T-IDDM project. Computer Methods and Programs in Biomedicine 69, 147–161 (2002)
3. Grant, R.W., Buse, J.B., Meigs, J.B.: Quality of diabetes care in U.S. academic medical centers: Low rates of medical regimen change. Diabetes Care 28, 337–442 (2005)
4. Shah, B.R., Hux, J.E., Laupacis, A., Zinman, B., van Walraven, C.: Clinical inertia in response to inadequate glycemic control: Do specialists differ from primary care physicians? Diabetes Care 28, 600–606 (2005)
5. American Diabetes Association: American Diabetes Association Complete Guide to Diabetes. 4 edn. Bantam, New York (2006)
6. Bichindaritz, I., Marling, C.: Case-based reasoning in the health sciences: What's next? Artificial Intelligence in Medicine 36, 127–135 (2006)
7. López de Màntaras, R., Arcos, J.L.: AI and music from composition to expressive performance. AI Magazine 23, 43–58 (2002)
8. Marling, C.R., Petot, G.J., Sterling, L.S.: Integrating case-based and rule-based reasoning to meet multiple design constraints. Computational Intelligence 15(3), 308–332 (1999)
9. Bridge, D., Göker, M., McGinty, L., Smyth, B.: Case-based recommender systems. The Knowledge Engineering Review 20, 315–320 (2005)
10. Bichindaritz, I.: MNAOMIA: Improving case-based reasoning for an application in psychiatry. In: Artificial Intelligence in Medicine: Applications of Current Technologies, Stanford, CA. Working Notes of the AAAI 1996 Spring Symposium (1996)
11. Bichindaritz, I., Kansu, E., Sullivan, K.M.: Case-based reasoning in CAREPARTNER: Gathering evidence for evidence-based medical practice. In: Smyth, B., Cunningham, P. (eds.) EWCBR 1998. LNCS (LNAI), vol. 1488, pp. 334–345. Springer, Heidelberg (1998)
12. Montani, S., Portinale, L., Leonardi, G., Bellazzi, R.: Applying case-based retrieval to hemodialysis treatment. In: McGinty, L. (ed.) Workshop Proceedings of the Fifth International Conference on Case-Based Reasoning, Trondheim, Norway (2003)
13. Marling, C., Whitehouse, P.: Case-based reasoning in the care of Alzheimer's disease patients. In: Aha, D.W., Watson, I. (eds.) ICCBR 2001. LNCS (LNAI), vol. 2080, pp. 702–715. Springer, Heidelberg (2001)
14. Marling, C., Shubrook, J., Schwartz, F.: Towards case-based reasoning for diabetes management. In: Wilson, D.C., Khemani, D. (eds.) ICCBR 2007. LNCS (LNAI), vol. 4626, pp. 305–314. Springer, Heidelberg (2007)
15. Schwartz, F.L., Shubrook, J.H., Marling, C.R.: Use of case-based reasoning to enhance intensive management of patients on insulin pump therapy. Journal of Diabetes Science and Technology (in press, 2008)
16. Montani, S., Bellazzi, R.: Supporting decisions in medical applications: The knowledge management perspective. International Journal of Medical Informatics 68, 79–90 (2002)

17. Montani, S., Magni, P., Bellazzi, R., Larizza, C., Roudsari, A.V., Carson, E.R.: Integrating model-based decision support in a multi-modal reasoning system for managing type 1 diabetic patients. Artificial Intelligence in Medicine 29, 131–151 (2003)
18. Popow, C., Horn, W., Rami, B., Schober, E.: VIE-DIAB: A support program for telemedical glycaemic control. In: Dojat, M., Keravnou, E.T., Barahona, P. (eds.) AIME 2003. LNCS (LNAI), vol. 2780, pp. 350–354. Springer, Heidelberg (2003)
19. Gómez, E.J., Hernando, M.E., García, A., del Pozo, F., Cermeno, J., Corcoy, R., Brugués, E., de Leiva, A.: Telemedicine as a tool for intensive management of diabetes: the DIABTel experience. Computer Methods and Programs in Biomedicine 69, 163–177 (2002)
20. Hernando, M.E., Gómez, E.J., Gili, A., Gómez, M., García, G., del Pozo, F.: New trends in diabetes management: Mobile telemedicine closed-loop system. In: Duplaga, M., Zielinski, K., Ingram, D. (eds.) Transformation of Healthcare with Information Technologies. IOS Press, Amsterdam (2004)
21. Biermann, E., Dietrich, W., Rihl, J., Standl, E.: Are there time and cost savings by using telemanagement for patients on intensified insulin therapy? A randomised, controlled trial. Computer Methods and Programs in Biomedicine 69, 137–146 (2002)
22. Lehmann, E.D.: AIDA (2008) (accessed February, 2008), `http://www.2aida.net/welcome/`
23. Lehmann, E.D.: Research use of the AIDA www.2aida.org diabetes software simulation program: A review. Part 1. Decision support testing and neural network training. Diabetes Technology & Therapeutics 5, 425–438 (2003)
24. Boutayeb, A., Chetouani, A.: A critical review of mathematical models and data used in diabetology. Biomedical Engineering Online 5 (2006)
25. Schmidt, R., Montani, S., Bellazzi, R., Portinale, L., Gierl, L.: Case-based reasoning for medical knowledge-based systems. International Journal of Medical Informatics 64, 355–367 (2001)
26. Nilsson, M., Sollenborn, M.: Advancements and trends in medical case-based reasoning: An overview of systems and system development. In: Proceedings of the Seventeenth International Florida Artificial Intelligence Research Society Conference – Special Track on Case-Based Reasoning, pp. 178–183. AAAI Press, Menlo Park (2004)
27. Holt, A., Bichindaritz, I., Schmidt, R., Perner, P.: Medical applications in case-based reasoning. The Knowledge Engineering Review 20, 289–292 (2005)