Predicting Postprandial Glucose Excursions Using Gaussian Process Regression

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Introduction

In recent years, continuous glucose measurement (CGM) devices have increased the quantity of data available to a patient and care team by an order of magnitude. We believe that a thorough evaluation of the control strategy of a patient or artificial pancreas can only occur when blood glucose measurements can be placed in the context of the patient's behaviors. Exciting results from the Juvenile Diabetes Research Foundation CGM study demonstrate a reduction in hemoglobin A1c when using CGM in intensive treatment in adults,[1] but we believe that the potential value of this technology has yet to be reached. Augmenting CGM data with lifestyle data can also help address the data overload problem.[2] In this letter, we present initial results using Gaussian process regression to predict 2-hour postprandial blood glucose using patient behavior data.

The intelligent diabetes assistant (IDA) is a telemedicine diabetes management system composed of three parts: data collection equipment used by the patient, a database, and a Web interface for the care team. Because the system is designed to capture lifestyle data along with glucose measurements, it is applicable for assisting with the management of type 1 and type 2 diabetes. The IDA system was designed to measure a patient's behavior and learn models that link actions to some outcome.

A custom data collection application that runs on a mobile phone is used to collect blood glucose measurements, images of meals, time and dose of medications, and messages. **Figure 1** displays screen shots of the glucose, meal image, and insulin injection collection applications. **Figure 2** displays a screen shot of the meal image nutrition analysis Web interface. IDA also collects continuous estimates of energy expenditure using the SenseWear Pro® armband from BodyMedia.

The primary focus for diabetes modeling in recent years has been for model predictive control in an artificial pancreas system.[3,4] IDA can aid in the development of an artificial pancreas through controller performance monitoring using its telemedicine capabilities; in this case, learning a model to predict potential controller problems using behavior data.

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Abbreviations: (CGM) continuous glucose measurement, (IDA) intelligent diabetes assistant

Keywords: glucose modeling, regression, telemedicine

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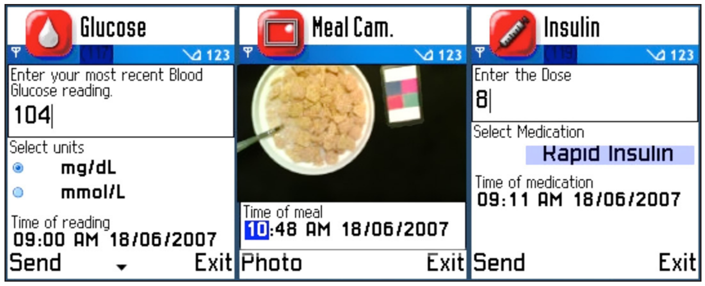

Figure 1. Screen shots of glucose, meal image, and insulin injection collection applications.

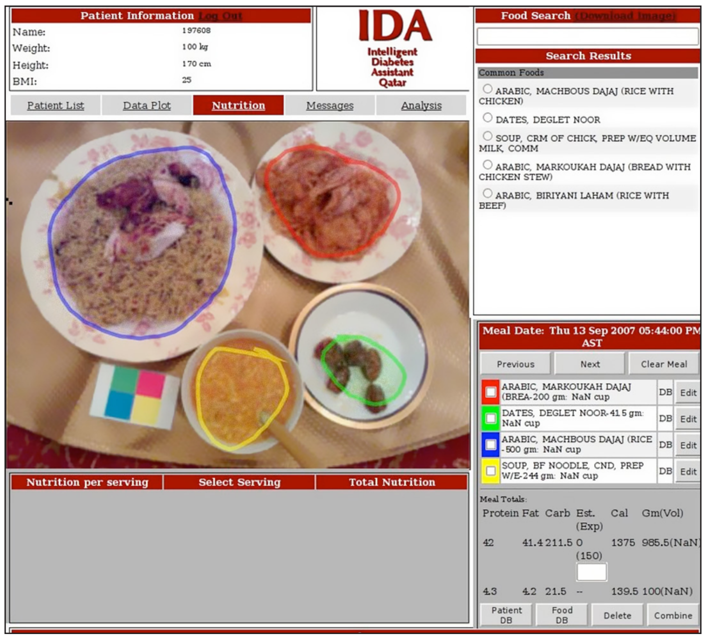

Figure 2. A screen shot of the meal image nutrition analysis Web interface.

Initial Results

Our initial study with IDA was designed to predict the impact that behaviors around meal times have on 2-hour postprandial glucose. The theoretical upper bound of predictions in region A of the Clarke error grid for this problem was estimated to be 43.6%.[5] Accuracies of up to 51% have been reported in practice.[6] For this experiment, 10 diabetes patients (six male, four female, ages 37 to 56) were recruited under the review of the Hamad Medical Corporation Research Committee (#7017/07) and the Carnegie Mellon University Institutional Review Board (HS08-139) in compliance with the Helsinki Declaration. Patients were informed about the research project, including the potential risks, and consent forms were signed. The data collection system was used by patients to collect 2 weeks of data. Patients were instructed to follow their current self-management plan as prescribed by their personal physician while collecting data.

We used Gaussian process regression to predict 2-hour postprandial blood glucose values based on the patient's meal intake, exercise, medication, and premeal glucose measuement. **Figure 3** contains the Clarke error grid plot of our predictions. In our initial results, 65.7% of our predictions were in region A.

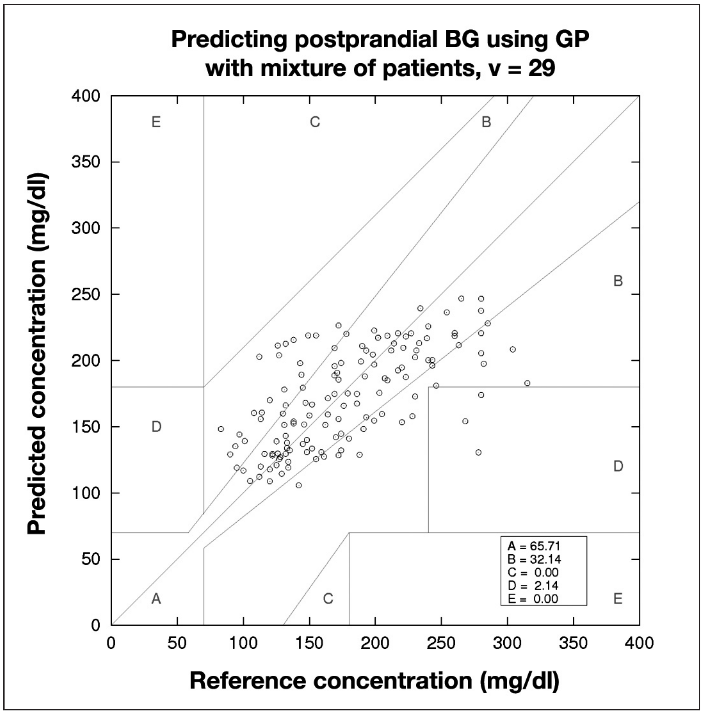

Figure 3. The Clarke error grid plot. BG, glood glucose; GP, Gaussian process.

Acknowledgment:

Support was received from QNRF NPRP #29-63-7-43.

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