[0030] FIG. 8 is a table illustrating root mean squared errors (RMSEs) and prediction time lags for DexCom study subjects tested using different models from three validation scenarios;

[0031] FIG. 9A illustrates a graph including raw and smoothed glucose signals;

[0032] FIG. 9B illustrates a graph including 30-minute-ahead predictions for four different models;

[0033] FIG. 10 illustrates a graph including a error grid analysis scatter plot for the four model predictions in FIG. 9B;

[0034] FIG. 11 is a table illustrating the cumulative number of hypo- and hyperglycemic episodes and related statistics (averaged over the corresponding subjects) for the raw, smoothed, and predicted data for each of the three studies; and

[0035] FIG. 12 illustrates a graph including the power spectrum density profiles for three studies.

V. DETAILED DESCRIPTION OF THE DRAWINGS

[0036] Exemplary, non-limiting, embodiments of the present invention are discussed in detail below. While specific configurations are discussed to provide a clear understanding, it should be understood that the disclosed configurations are provided for illustration purposes only. A person of ordinary skill in the art will recognize that other configurations may be used without departing from the spirit and scope of the invention.

[0037] An embodiment of the invention utilizes similarities in the short-term (30-minute or less) dynamics of glucose regulation in different diabetic individuals to develop a single, universal autoregressive (AR) model for predicting future glucose levels across different patients. Data are collected from three different studies, involving subjects with both type 1 and 2 diabetes and using three different continuous glucose monitoring (CGM) (or glucose monitoring device) devices: iSense (iSense Corporation, Wilsonville, Oreg.), Guardian RT (Medtronic Inc., Northridge, Calif.), and DexCom (DexCom Inc., San Diego, Calif.). Data-driven AR models of a fixed order are developed for each subject; and, the AR models are tested on data from other subjects from the same and from different studies. The RMSE and prediction time lag are used as metrics to quantify the models' performance; and, the resulting AR coefficients from the different models developed for each subject are compared.

[0038] The developed AR models (i.e., the AR model coefficients) are not significantly dependent on a given individual, diabetes type, age, or CGM device. Thus, universal, individual-independent predictive models are developed, which reduces the burden of model development as one model can be used to predict future glucose levels in any individual using any CGM device. Such predictive models are utilized together with CGM devices for proactive regulatory therapy.

[0039] An embodiment of the invention provides a system for predicting future glucose levels in an individual. The system includes a glucose monitoring device for obtaining time-series data representing glucose levels measured at fixed time intervals from an individual patient. The time-series data is input into a universal AR model having a plurality of model coefficients. As described more fully below, the model coefficients are invariant among patients (i.e., patient/individual independent). In predicting future glucose levels, the model coefficients weight the importance of the previously measured glucose levels (e.g., a more recent measurement may be more important than an older measurement). Thus, each of the measured glucose levels input from the glucose monitoring device is multiplied by a respective model coefficient of the AR model. The models of the embodiments herein use the invariant model coefficients to develop a universal AR model that is portable from individual-to-individual.

[0040] The invention in at least one embodiment provides a prediction of a future glucose level. This embodiment uses a desired prediction horizon time for determining the number of times the model is used to process a sliding window of predicted and real glucose levels that advances one sample period per iteration. Each advance removes the oldest glucose level and slides the remaining glucose levels to the next coefficient.

[0041] FIG. 1A is a flow diagram illustrating a method for predicting at least one future glucose level in an individual according to an embodiment of the invention. The method receives glucose signals from a glucose measuring device, wherein the glucose signals represent glucose levels obtained from the individual at fixed time intervals (110). For example, in order to predict glucose levels of an individual 30 minutes into the future, glucose levels will need to have been measured for the individual for 30 sampling periods and a number of prediction iterations of the model will be required (e.g., 7 iterations if 5-minute sampling and 31 iterations if 1 minute sampling). The glucose signals are converted into numerical values representing the glucose levels obtained from the individual (112). The glucose signals and/or numerical values are stored in a memory unit housed in the glucose measuring device (114). In another embodiment, the memory unit is external to the glucose measuring device.

[0042] The method predicts the individual's future glucose levels by weighing the stored glucose signals by model coefficients of a glucose prediction function (120). The predicting of the future glucose levels is performed with a processor having code to perform calculations of the glucose prediction function.

[0043] The glucose prediction function is a universal autoregressive model that is portable between individuals irrespective of health of the individuals. The health of the individual includes a diabetes type of the individual, age of the individual, and/or whether the individual is hospitalized. As described more fully below, the glucose prediction function in at least one embodiment is trained using test subjects that include children, adults, and the elderly having type I diabetes and type II diabetes. Moreover, the glucose levels of the test subjects were obtained using three different types of glucose measuring devices. Thus, the model coefficients of the glucose prediction function are invariant between the individuals irrespective of the type of the glucose measuring device utilized to measure the glucose signals. FIG. 5B is a table illustrating the ranges for each of the thirty model coefficients according to at least one embodiment of the invention.

[0044] FIG. 9B illustrates future glucose levels predicted by glucose prediction functions according to an embodiment of the invention. The tightness of the data points illustrate that the weighing of the previous glucose signals of the individual by the model coefficients reduces a time lag of the predicted future glucose levels (see also FIGS. 6-8 for actual time lags for 34 glucose prediction functions developed using training data from 34 test subjects).

[0045] In addition, the method displays the predicted future glucose levels on a display (130) and generates an alert (or other notification) when a future glucose level is predicted to