Fault Detection in Continuous Glucose Monitoring Sensors for Artificial Pancreas Systems

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Abstract: Continuous glucose monitoring (CGM) sensors are a critical component of artificial pancreas (AP) systems that enable individuals with type 1 diabetes to achieve tighter blood glucose control. CGM sensor signals are often afflicted by a variety of anomalies, such as biases, drifts, random noises, and pressure-induced sensor attenuations. To improve the accuracy of CGM measurements, an on-line fault detection method is proposed based on sparse recursive kernel filtering algorithms to identify faults in glucose concentration values. The fault detection algorithm is designed to effectively handle the nonlinearity of the measurements and to differentiate the normal variability in the glycemic dynamics from sensor anomalies. The effectiveness of the proposed recursive kernel filtering algorithm for sensor error detection is demonstrated using simulation studies.

Keywords: Kernel filtering algorithms, sparsification, faults detection, sensor errors, artificial pancreas.

1. INTRODUCTION

Continuous glucose monitoring (CGM) sensors are a critical component in the closed-loop control of blood glucose concentrations for people with type 1 diabetes (T1D). Although less accurate than conventional handheld glucose meters, real-time CGM sensors provide necessary feedback through frequent measurements (typically every 5 mins) for artificial pancreas (AP) systems while being minimally invasive, thus enabling individuals with T1D to regulate their glucose levels throughout their daily lives (Kirchsteiger, Jørgensen, Renard, & Del Re, 2015). The CGM sensors incorporate a disposable probe implanted under the skin and a transmitter placed above the skin. The implanted probe an electrical signal proportional measures to the concentration of glucose present in the interstitial fluid of the subcutis. Due to the constant interaction of the probe with the interstitial fluid, the sensitivity of the CGM sensor may vary over time (Andrea Facchinetti, Del Favero, Sparacino, & Cobelli, 2011). Therefore, CGM sensors occasionally require recalibration with finger-stick glucose measurements obtained using a handheld glucose meter (Deiss et al., 2006; Group, 2008; Klonoff, 2005). CGM sensors also routinely encounter faulty measurements due to incorrect sensor calibrations (bias and step faults) (K. Turksoy, Roy, & Cinar, 2017), fouling (slow drift or gradual deterioration in sensor communication disruptions, measurements). subject movements, dislodging or displacement of the sensor from underneath the skin, and pressure-induced sensor attenuations

(PISA) (Baysal et al., 2014; A. Facchinetti, Del Favero, Sparacino, & Cobelli, 2016). Such faults need to be appropriately detected and reconciled to avoid feedback control based on abnormal sensor readings (Feng, Turksoy, Samadi, Hajizadeh, & Cinar, 2016).

A number of studies have addressed faults in AP systems in general, and CGM sensors in particular. Early efforts in handling faults in AP systems include an on-line failure detection method that employs state-space dynamic models and Kalman filters to improve overnight safety of people with T1D (Andrea Facchinetti et al., 2011; A. Facchinetti et al., 2016; Andrea Facchinetti, Favero, Sparacino, & Cobelli, 2013). Overnight AP safety is of particular concern because sensor inaccuracy can lead to critical situations when the patient is asleep and cannot readily rectify the sensor errors. In recent work, a real-time fault detection method is proposed based on robust Kalman filter and latent variable regression models to distinguish between abnormal signal readings and normal transient variations in sensor measurements caused by changes in the underlying metabolism of individuals (Feng et al., 2016; K. Turksoy et al., 2017). The notions of robustness are also used to develop a model-based fault detection technique based on interval analysis to account for uncertainty in the model and detect disconnections of the insulin infusion set (Herrero et al., 2012). Various statistical monitoring charts and latent variable analysis techniques are also developed to detect erroneous CGM measurements (Zhao & Fu, 2015). In some previous CGM sensor fault

detection approaches, information of insulin delivery is used. The insulin infusion information, however, may not be available when the CGM sensor is used in the conventional multiple daily insulin injection therapy. Furthermore, the insulin infusion information may also be faulty if the infusion pump experiences faults due to blockages or insulin leakage to the infusion site. Using the inaccurate insulin infusion information to detect faults in CGM measurements may lead to incorrect conclusions, especially if the infusion pump fails to deliver the instructed dose of insulin. Some methods also use off-line analysed blood samples for comparison to detect failures in the CGM signal, though off-line blood sampling may not always be practical for detecting sensor faults, especially overnight when the individual is asleep. To avoid confounding the possibly inaccurate insulin infusion information with sensor error detection, a method that can identify the abnormalities in CGM sensors based only on CGM data is of interest. Moreover, distinguishing the sensor errors from the normal fluctuations in the CGM measurements due to diurnal variability is important for reliable fault detection.

Motivated by the above considerations, a method is proposed in this work to detect in real-time failures in CGM sensors that may be lead to misleading information and consequently compromise the effectiveness of insulin therapy. The proposed sensor fault detection approach relies solely on signals from the CGM sensor to avoid confounding information from other variables that may also experience faults. The proposed approach uses a sparse kernel filtering algorithm based on approximate linear dependency (ALD) to identify a model, and the analytical redundancy within the model is exploited to detect sensor faults. Appropriate thresholds are also specified to distinguish between the abnormal measurements and the typical glycemic variability. The reminder of the article is structured as follows. The sparse kernel filtering algorithm based on the ALD criterion is described in Section 2. Then, Section 3 provides a detailed description of the approach for online faults detection, followed by a discussion of the simulation results in Section 4. Concluding remarks are provided in Section 5.

2. KERNEL-BASED MODELING ALGORITHM

The kernel-based adaptive filtering algorithms provide an elegant and efficient method for handling the nonlinearity in the data. Based on the framework of reproducing kernel Hilbert spaces (RKHS), the Mercer kernels are applied to yield the nonlinear versions of the kernel-based filtering algorithms. As such, the conventional linear algorithms are transformed to their respective nonlinear versions with efficient quadratic objectives that can easily be recursively updated as more data becomes available. To this end, the original input data \mathbf{u}_i from input space U is mapped nonlinearly to a high-dimensional feature space H as follows:

$$U \mapsto H$$
$$\mathbf{u}_i \mapsto \kappa(\mathbf{u}_i, \cdot)$$
(1)

The input space U is a compact of i, $\kappa: U \times U \rightarrow i$ is a positive definite kernel and the high-dimensional feature space H is the RKHS. The inner products can be computed through a positive definite and symmetric kernel function (Vapnik, 2013)

$$\kappa\left(\mathbf{u}_{i},\mathbf{u}_{j}\right) = \left\langle \kappa\left(\mathbf{u}_{i},\cdot\right),\kappa\left(\mathbf{u}_{j},\cdot\right)\right\rangle_{H}, \quad \mathbf{u}_{i},\mathbf{u}_{j} \in U$$
(2)

In Mercer's condition, different kinds of kernels, such as projective kernels and radial kernels, can be directly applied to compute the inner products involved in the RKHS. Among these kernels, the Gaussian kernel function given by

$$\kappa\left(\mathbf{u}_{i},\mathbf{u}_{j}\right) = \exp\left(-\frac{\left\|\mathbf{u}_{i}-\mathbf{u}_{j}\right\|^{2}}{2\sigma^{2}}\right)$$
(3)

is commonly applied. In such kernel-based regression techniques, a nonlinear mapping is evaluated as a linear combination of a given kernel $\kappa : U \times U \rightarrow i$ and input dataset $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n\} \in U$ (Schölkopf & Smola, 2002), which also can be seen as a growing RBF-like network (Liu, Park, & Principe, 2009)

$$\varphi\left(\cdot\right) = \sum_{i=1}^{n} \omega_{i} \kappa\left(\mathbf{u}_{i},\cdot\right)$$
(4)

Note that the above function is still linear in the coefficients ω_i stored in memory during training.

To define the kernel-based learning algorithm, consider the problem of least squares regression in an off-line scenario with available input-output data $\{\mathbf{u}_i, d_i\}_{i=1}^n$. Further, denoting the coefficient vector $\boldsymbol{\omega} = [\omega_1, \omega_2, \cdots, \omega_n]^T$, the kernel-based learning process can be defined as solving for the value of the weights $\boldsymbol{\omega} \in i^{-n}$ that minimize the quadratic objective

$$\min_{\boldsymbol{\omega} \in j^{n}} \left\| \mathbf{d} - \mathbf{K} \boldsymbol{\omega} \right\|^{2} + \lambda \boldsymbol{\omega}^{T} \mathbf{K} \boldsymbol{\omega}$$
 (5)

where $\mathbf{d} = [d_1, d_2, \dots, d_n]^T \in i^{-n}$ is the target vector of the training data, $\mathbf{K} \in i^{-n \times n}$ is the Gram matrix with elements $K_{ij} = \kappa (\mathbf{u}_i, \mathbf{u}_j)$, and λ is a regularization parameter. The problem in (5) can be explicitly evaluated in closed form, and the solution is

$$\boldsymbol{\omega} = \left(\mathbf{K} + \lambda \mathbf{I}\right)^{-1} \mathbf{d} \tag{6}$$

where ${\bf I}$ denotes the identity matrix of appropriate dimension.

In the kernel recursive least squares (KRLS) algorithm (Engel, Mannor, & Meir, 2004), the above least squares problem is formulated in the high-dimensional feature space H, and the inner products in RKHS can be calculated using various kernel functions. Then the weighted cost function of

KRLS can be defined as finding the weight vector $\boldsymbol{\omega}$ that minimizes the quadratic cost function

$$\min_{\boldsymbol{\omega} \in j^{n}} \sum_{j=1}^{n} \left| \boldsymbol{d}_{j} - \boldsymbol{u}_{j}^{T} \boldsymbol{\omega} \right|^{2} + \lambda \left\| \boldsymbol{\omega} \right\|^{2}$$
(7)

The aim of the KRLS algorithm is to update this solution recursively as new data $\{\mathbf{u}_{n+1}, d_{n+1}\}$ become available (Liu, Principe, & Haykin, 2011).

In contrast to the conventional linear recursive least squares algorithm that is based on a covariance matrix of fixed dimension, the dimension of the kernel function in KRLS increases as the number of data samples increase. The incrementally augmented kernel matrix in (6) thus causes computational complexity to increase and memory requirements for information storage to intensify. Moreover, the higher dimension of vector ω may also lead to overfitting of the training data.

To overcome this drawback, sparsification methods based on the information theoretic approach are often used in the kernel-based on-line learning algorithms. The basic idea of the sparsification methods is to prevent the size of kernel functions κ from becoming prohibitively large. Over the past decade, several sparsification criteria for selecting a finite proper dictionary are employed in formulating KRLS algorithms. Employing the finite dimensional summary of the training data, the reduced-order model can be written as (Liu et al., 2011)

$$\varphi\left(\cdot\right) = \sum_{i=1}^{m} \omega_{i} \kappa\left(\tilde{\mathbf{u}}_{i},\cdot\right)$$
(8)

In this expression, the sparse dataset $\{\tilde{\mathbf{u}}_1, \tilde{\mathbf{u}}_2, \cdots, \tilde{\mathbf{u}}_m\}$ is a subset of the original dataset $\{\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_n\}$ with $m \square n$. As the new finite proper dictionary a result, $\tilde{D} = \{\kappa(\tilde{\mathbf{u}}_1, \cdot), \kappa(\tilde{\mathbf{u}}_2, \cdot), \cdots, \kappa(\tilde{\mathbf{u}}_m, \cdot)\}$ is composed of a subset of of the samples original dictionary $D = \{\kappa(\mathbf{u}_1, \cdot), \kappa(\mathbf{u}_2, \cdot), \cdots, \kappa(\mathbf{u}_n, \cdot)\}$ such that the new finite dictionary is sufficient to characterize the relationships among the variables in the complete dataset. One approach for constructing on-line the compact dictionary is through recursive updating, which typically involves iteratively evaluating whether the new kernel function $\kappa(\mathbf{u}_{n}, \cdot)$ is appropriate for including in the sparse subset. Therefore, for each new data sample, an admission criterion is required to determine whether the input vector should be admitted to the finite dictionary or omitted. One of the commonly used sparsification criteria is the approximate linear dependency (ALD) criterion (Engel et al., 2004), which is also considered in this work for modelling the CGM measurements.

In the ALD criterion (Engel et al., 2004), the new kernel function $\kappa(\mathbf{u}_{n+1}, \cdot)$ of a newly available data sample \mathbf{u}_{n+1} is admitted to the finite dictionary if the data sample cannot be written as an approximate linear combination of the kernel-

version of the previous data samples $\{\tilde{\mathbf{u}}_1, \tilde{\mathbf{u}}_2, \dots, \tilde{\mathbf{u}}_m\}$. To test the new sample, the ALD criterion evaluates the cost function

$$A_{n+1} \square \min_{\boldsymbol{\omega} \in i^{n}} \left\| \kappa \left(\mathbf{u}_{n+1}, \cdot \right) - \sum_{i=1}^{m} \boldsymbol{\omega}_{i} \kappa \left(\tilde{\mathbf{u}}_{i}, \cdot \right) \right\|^{2}$$
(9)

which quantifies the distance in the RKHS of the new data \mathbf{u}_{n+1} to the linear span of the data already present in the dictionary. The solution to the ALD criterion problem in (9) is given in the closed form as

$$A_{n+1} = \kappa \left(\mathbf{u}_{n+1}, \mathbf{u}_{n+1} \right) - \kappa \left(\tilde{\mathbf{u}}_{n}, \cdot \right) \tilde{\mathbf{K}}_{n}^{-1} \kappa \left(\tilde{\mathbf{u}}_{n}, \cdot \right)^{T}$$
(10)

where $\left[\tilde{\mathbf{K}}_{n}\right]_{i,j} = \kappa \left(\tilde{\mathbf{u}}_{i}, \tilde{\mathbf{u}}_{j}\right)$, $i, j = 1, \dots, m$, and

$$\boldsymbol{\kappa}\left(\tilde{\boldsymbol{u}}_{n},\cdot\right)=\left[\boldsymbol{\kappa}\left(\tilde{\boldsymbol{u}}_{1},\boldsymbol{u}_{n}\right),\boldsymbol{\kappa}\left(\tilde{\boldsymbol{u}}_{2},\boldsymbol{u}_{n}\right),\cdots,\boldsymbol{\kappa}\left(\tilde{\boldsymbol{u}}_{m},\boldsymbol{u}_{n}\right)\right].$$

After computing the ALD criterion for the samples, the thresholds v_1 and v_2 are used to evaluate whether the new data sample \mathbf{u}_{n+1} should be added to the finite dictionary or omitted. The ALD criterion is evaluated according to the following cases:

Case 1. $A_{n+1} \le v_1$: the new data sample \mathbf{u}_{n+1} is redundant, the dictionary is maintained unchanged;

Case 2. $v_1 < A_{n+1} < v_2$: the new data sample \mathbf{u}_{n+1} contains new information not present in the dictionary, thus add the new sample to dictionary and update the learning system;

Case 3. $A_{n+1} \ge v_2$: the new data sample \mathbf{u}_{n+1} is abnormal and should be further investigated, the dictionary is unchanged.

3. ONLINE DETECTION USING SPARSE KRLS ALGORITHM

Combining the KRLS algorithm with the ALD criterion, the online sparse variant of the KRLS algorithm is obtained and designated as ALD-KRLS. When applying the sparse kernel filtering algorithm for online fault detection, it is critical to specify proper threshold parameters to distinguish the faulty measurements from normal variability in the glycemic dynamics.

The threshold parameters are important for the effective implementation of the sparse filtering algorithms. However, the thresholds are problem-dependent parameters, and the choice of the thresholds is typically defined by the characteristics of the system. In the context of online glucose prediction, the following steps are provided to select appropriate thresholds for the ALD-KRLS algorithm:

- Step 1. Use a large v_1 to disable the detection of abnormal samples;
- Step 2. Use a small v_2 to disable the detection of redundant samples;
- Step 3. Train the model off-line to obtain an original data set and ALD index for the samples;

- Step 4. According to the characteristics of the CGM data, set the reasonable thresholds for the subsequent off-line training procedure. For instance, if the training dataset has 10% abnormal data and 50% redundant data, then v_1 can be chosen as the median value of the informatics index vector, and v_2 can be set as the value larger than 90% of the informatics index.
- Step 5. Use the new thresholds to retrain the detection model and obtain the sparse model for on-line fault detection.
- Step 6. After every N_{hyp} instances, re-estimate the thresholds of learning models.

The on-line fault detection method is as follows. The algorithm is initialized using training data, yielding an initial estimate of the model and the maximum capacity of dictionary is specified. Then, for online fault detection using the ALD-KRLS algorithm, the following steps are iterated for each new observation.

- Step 1. Compute the ALD criterion A_i for the new data sample {u_i, d_i}. For a one-step-ahead prediction horizon, the output d_i is the current CGM measurement sample u_{n+1}, and the input vector is the past sample u_i = u_n. Therefore, the new data pattern is {u_n, u_{n+1}}.
- Step 2. Evaluate the ALD criterion A_i :
 - Step 2.1. If $A_{n+1} \le v_1$: the new pair $\{\mathbf{u}_{n+1-H}, u_i\}$ is redundant for the current learning system, which means the current CGM measurement is reliable.
 - Step 2.2. If $v_1 < A_{n+1} < v_2$, the new pair $\{\mathbf{u}_{n+1-H}, u_i\}$ is learnable for current learning system, which means the current CGM measurement new information resulting from dynamic variability, not faults. The learning system can be updated and the new pair should be added in the dictionary;
 - Step 2.3. If $A_{n+1} \ge v_2$: the new pair $\{\mathbf{u}_{n+1-H}, u_i\}$ is abnormal, thus use the pseudo input $\hat{\mathbf{u}}_{n+1}$ instead of \mathbf{u}_{n+1} for online prediction and generate a failure alert.
- Step 3. If the AP system has meal, exercise, sleep announcement, the thresholds v_1 and v_2 may be reset as needed;
- Step 4. After every N_{hyp} sampling instances, re-estimate the parameters and thresholds v_1 and v_2 ;
- Step 5. Proceed to the next data sample.

4. RESULTS AND DISCUSSION

In this work, the proposed ALD-KRLS based sensor fault detection method is evaluated using the US Food and Drug Administration approved University of Virginia/Padova (UVa/Padova) metabolic simulator (Kovatchev, Breton, Dalla Man, & Cobelli, 2009). The simulations consist of 30 in silico subjects with T1D (ten adults, ten adolescents, and

ten children). Each subject is operated in closed-loop with a general predictive controller for glucose regulation (Kamuran Turksoy, Quinn, Littlejohn, & Cinar, 2014) and with a duration of six days. The same meal plan is used for adults and adolescents, and the amount of carbohydrates in meals is reduced for children. The sampling time of the CGM sensor is five minutes. The initial period of the collected CGM data is used for off-line training. Subsequently, the one-step-ahead prediction model is incorporated for real-time model adaption and online glucose prediction. For online model adaption, the desired response is unknown in real-time, though the current measurement can be used as a desired target for the last iteration to update the model.

For offline training, a glucose measurement from three days (864 samples) is used to estimate the algorithm parameters and identify an initial prediction model. The model order (length of input vector), represented by L, is specified as 6, and deemed to yield the best accuracy.

In order to demonstrate the effectiveness of the proposed approach, several types of sensor errors are considered in this work: biased signal, random noise, continuous drifts, step changes, and PISA.



Fig.1. Fault detection results for random noise in the CGM measurements. The magnitude of random noise is 10%.



Fig.2. Fault detection results for a drift change in the CGM measurements. The rate of the drift change is 20%.



Fig.3. Fault detection results for a step change in the CGM measurements. The size of the step change is 30%.

As shown in Fig. 1, a single random noise is added to the testing data, and the values of ALD index typically fluctuate around the -2.3 level, except when the fault occurs. As the measurements from CGM sensors are disturbed with random noise, the value of the ALD index increases above the average value. An alarm may be issued when the value of ALD index is larger than the threshold v_2 .

In Fig. 2, a single drift change is added to the CGM data. The fault detection results show that the ALD index increases when the sensor readings become abnormal. Because the ALD criterion can quantify the distance in the RKHS of the new input sample \mathbf{u}_{n+1} to the linear span of the data already present in the dictionary, the ALD index increases when the input data becomes abnormal. If the threshold value is specified appropriately, the fault alarm can be generated when the ALD index is larger than the threshold.

Next, a single step change is used to simulate sensor failures. For the step disturbances imposed onto the CGM sensor data, the fault detection results are shown in Fig. 3. Similarly, the fault detection method is sensitive to the erroneous sensor readings caused by the the step change. As all of these three simulations use data across multiple days, the glycemic trends include large variations in the glycemic dynamics caused by meals. Therefore, the simulation results indicate that the online fault detection method can accurately distinguish the abnormal data from the normal variability in the glycemic dynamics.

For the fault diagnosis procedure, the duration of the change in the ALD index can be indicative of the type of fault. If the change in the ALD index is short, lasting only one or two sampling instances, the sensor failure is due to random noise. If the increase in the ALD index persists for several consecutive sampling instances, the sensor failure is likely due to a drift or step change. With regards to the problem of loss of sensitivity, the values of the ALD index will be directly proportional with the degree of the sensitivity loss. Thus threshold v_2 is very important for the accurate detection while the duration of change in the ALD index can be used for diagnosing the faults.



Fig.4. Fault detection results for PISA (10%) at night-time.



Fig.5. Fault detection results for PISA (5%) at night-time.

Figs. 4 and 5 show the results for a high PISA (10%) and low PISA (5%), respectively. It is readily observed that the values of ALD index increase when PISA occurs. The comparison reveals that when less pressure is applied to the CGM sensors, the fault detection sensitivity decreases and the change in the ALD index is less pronounced. Therefore, the performance of fault detection approach is directly affected by the magnitude of the pressure applied on the CGM sensor. Overall, the simulation results demonstrate the capability of the proposed fault detection approach to identify the faulty CGM measurements from the normal variations in the glycemic dynamics.

Table 1. Summary of the performance for different faults.

Type of Faults	Fault Detection Rate (%)	False Alarm Rate (%)
Random Noise	81.3	29.7
Drift Change	78.9	33.5
Step Change	89.2	21.1
PISA (10%)	72.1	37.9
PISA (5%)	65.8	40.9

Table 1 summarizes of the fault detection performance of the method for various types of faults (biased signal, random noise, continuous drifts, step changes, and PISA). The performance of the proposed approach is quantitatively evaluated using the fault detection and false alarm rates. The fault detection rate represents the percentage of faulty samples that are correctly identified as faulty, while the false alarm rate represents the percentage of normal samples that are incorrectly identified as faulty. Overall, despite the presence of significant disturbances such as meals and variations in glycemic dynamics, the proposed approach can detect various types of faults in the CGM sensors with reasonable accuracy.

5. CONCLUSION

In this work, an on-line fault detection method is proposed to improve the accuracy of CGM measurements. The fault detection algorithm, based on sparse kernel filtering algorithms to identify erroneous sensor readings of the CGM measurements, is designed to effectively handle the nonlinearity of the data and to differentiate the normal variability in the glycemic dynamics from sensor anomalies. Simulation case studies demonstrate the effectiveness of the proposed recursive kernel filtering algorithm for sensor error detection.

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