Un- Interrupted Glucose Monitoring and Prediction by Using Smart Sensor System

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Abstract- The monitoring of real time Blood Glucose level in diabetes patient is a big problem to be addressed in near future to treat patients efficiently. There are some kind of the Continuous Glucose Monitoring (GCM) sensors available in market but very expensive to use for long term to monitor glucose level continuously. To overcome this problem a combination of the real time monitoring of glucose is used to predict the glucose concentration at a particular time. There are various prediction techniques are available and used to predict glucose concentration in blood. For the purpose of prediction of glucose level in this research, four different parameters are considered to predict glucose concentration by using Kriging prediction algorithm. First, the CGM data is calibrated accurately. Secondly, the CGM data is filtered to increase signal-to-noise ratio (SNR). Thirdly, prediction of future glucose concentration is predicted by using appropriate modeling techniques. Based on the study and experimentation Kriging based algorithm for prediction is performed very well as compared to other prediction technique with the lowest mean square error.

Manuscript received April 5, 2019
Manuscript revised April 20, 2019

Key works: Continue Glucose Monitoring, Blood Glucose, Vector Support Engine, Root Mean Square Error, Weight Factor

1. INTRODUCTION

In the second half of the last century diabetes patient increased exponentially in the world and governments are spending billions of dollar every year to treat the patients. Un-interrupted glucose monitoring sensor systems are available to monitor the blood sugar continually for several days (max. 14 days). Continues monitoring systems measures the glucose level every 5 to 10 minutes and sent the reading to portable device (IPad, Mobile, etc.) by using Bluetooth communication. In the figure below CGM sensor is planted to the arm of the patient for monitoring glucose level continually.

In the beginning of this century, the first continues glucose monitoring sensor system was introduced and the instrument was used to monitor glucose concentration and last for up 72 hours consecutively with the purpose of enhancing knowledge about blood sugar variations and dynamic, skimpy hypoglycemic and hyperglycemic episodes that were difficult to detect by using sparse SMBG measurements [27].

As continues glucose monitoring sensor system is improved by embedding new properties of the real-time measurement of blood sugar and its fluctuations.

Figure 1: Continue Glucose Monitoring Sensor

For preventing hypoglycemia and better control of blood glucose levels, it is necessary to monitoring and measure the glucose level at regular intervals and patient profiles should be available online for the corresponding health professionals. By self-monitoring the glucose levels by individuals and updating the personal profile will give benefit to control glucose level in blood. By maintaining the individual profile of the patient it will give the edge to the doctors for better treatment plan. Also, it will enable the family and patient to update the patient everyday diet plan physical activities and medicine dose. [1]

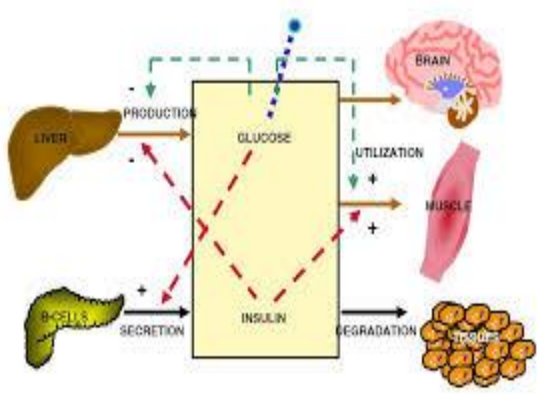

Figure 2: Insulin producing organ in human body

But on the other hand it is very hard to measure the glucose level regularly and it is not possible the patient to carry blood glucose monitor with him 24/7.The measurement of BG of the patient is varies due to the health conditions and other factors. Most doctors suggest and agree the patient who are on insulin need to measure glucose level every six to eight hours daily, usually during fasting, just before taking meals and just before going bed for sleeping in the night. But sometimes it is hard to monitor regularly, but, it is possible that patients cannot often maintain this control, because working hours or travels. Due to these reasons the correct prediction of the blood sugar is very much important for self-monitoring and self-administering the health situations. A lot of research has been done into the automatic prediction of blood glucose using machine learning algorithms. There has been lot research work is done by researcher for automatic blood Glucose prediction by using different algorithm developed by the researcher. For example, in the Artificial Pancreas Project [2], blood sugar level is predicted for the better insulin flow in the patient body to regulate the blood sugar in the body. Regardless of the research work done by researcher to predict BG level correctly and made recommendations for individuals. The prediction models which exist can be categorized as population based prediction [3–6] or patient-based prediction [7–10].

Kriging prediction techniques are used in different type of problems e.g. signal coverage, temperature prediction, location prediction and mineral prediction [11-13].

In [14-15], author used the Kriging prediction technique to predict coverage and location by using ground and aerial sensor along with Kriging prediction. This topic need to consider to solve the problem of diabetes to reduce the death risk. Millions of dollars have spent to provide medical services to the diabetes patients. Every year two million people died in 2017 due to diabetes and this number quoted by World Health Organization (WHO) in document released on 17th November 2017.The number of diabetes patients has increasing day by day and in 2017, 8.8% of the total world population has diabetes which is 700 million and it is forecasted in 2045 the number diabetes patient will touch one billion. The above explained topic is very important to be considered as research topic and provide a better and cheaper solution to monitor the blood glucose level of the patient.

According the studies of some organizations, there is 336 million people are affected by diabetes. The number is expected to rise to 550 million by 2030 according the world health organization. Due to diabetes, there 4.6 million death every year or one diabetic patient dies every 7 seconds. It is one of the top ten reasons which cause disability and other heart problems and stroke and blindness. Unluckily, 50 percent of people with diabetes are undiagnosed.

Figure 3: Diabetic monitoring system by using CGM sensor and mobile application

The researchers have proposed several algorithms for the blood glucose prediction by using different techniques. Kriging interpolation techniques is used in this research work to predict the blood glucose level by using real time data for last 24 hours. The real time blood glucose is measured by using the sensor system which is already available in the market for the continue glucose monitoring. The measured data is used to predict the glucose level in the patient body ahead and mean square error is calculated.

In ordinary Kriging, a spatial phenomenon Z is assumed to be represented by its realizations $Z(t_1), Z(t_2) \ldots Z(t_n)$ at time $t_1, t_2 \ldots t_n$. Then the Kriging interpolator of Z at time t_0 is given below

$$\hat{Z}(t_0) = \sum_{i=1}^{n}\left(\lambda_i Z(t_i)\right),$$

where λ_i are the weights fulfilling the normalization condition, i.e., $\sum_{i=1}^{n}(\lambda_i) = 1$ and the expected error is $E[\hat{Z}(t_0) - Z(t_0)] = 0$ as used. The Kriging technique provides an optimal estimate in the sense that it minimizes the estimation variance and is unbiased as described by [12].

It can be shown that the optimal weights λ_i for the Kriging interpolator can be computed from the following system of linear equations as described by [12].

$$\Lambda = A^{-1} B,$$

$$\begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_n \end{pmatrix} = \begin{pmatrix} \gamma(t_1,t1) \ldots\ldots \gamma(t_1,t_n) \\ \vdots \\ \gamma(t_n,t_1) \ldots\ldots \gamma(t_n,t_n) \end{pmatrix}^{-1} \begin{pmatrix} \gamma(t_1,t^*) \\ \vdots \\ \gamma(t_n,t^*) \end{pmatrix},$$

where Λ is a vector comprising the weights, A is the spatial correlation matrix of sample with time difference $t_1, t_2, \ldots, t_n$ and b is a vector whose elements represent the spatial correlation between t_0 and each t_i $\{t_1, t_2, \ldots, t_n\}$. All correlations are based on an appropriate variogram model defined for the spatial phenomenon under observation as described by [14].

In this research work above explained problem in existing approaches are addressed by using real time patient data analysis and Kriging prediction to improve the prediction of blood sugar up to one hour. In this research work personalized real time data based predictive model is proposed to predict patient blood glucose level automatically based on their daily activities collected from their digital devices.

2. Literature Review

Recently data released by World Health Organization (WHO) shows that, 347 million people died due to diabetes in last year [16]. In 2006, about 3.7 million people were died due to high fasting glucose level and WHO estimated that diabetes will be the 7th foremost reason of death in 2030. In financial terms, the costs for diabetes are estimated at $ 245 million in 2012 in USA [17], while they range from 6 to 14% of the total health expenditure in EU countries [18]. The explanations on diabetes are considered as more serious socio-sanitary emergencies for the treatment of the 3rd millennium [19], due to this reason innovative methodologies are very much needed to tackle this issue. This is because Continuous Glucose Monitoring (CGM) sensors are getting more importance than ever, CGM was available in the market since the start of 21st century, is emphasized, together with a short description of minimally invasive and non-invasive CGM devices.

Figure below shows the Dexcom sensor for continues glucose monitoring and it lasts for 7 days and it cost around $150.

Figure 4: Dexcom Glucose monitoring via mobile application by using CGM

The number of diabetes patients has increasing day by day and in 2017, 8.8% of the total world population has diabetes which is 700 million and it is forecasted in 2045 the number diabetes patient will touch one billion.

Lot of research is done to study the risk prediction for diabetes patients. Artificial neural network based prediction model is proposed in [23], to predict the onset of diabetes mellitus in the Indian female population of Pima near Phoenix, Arizona. More recently, Choi et al. two models of pre-diabetes screening using an artificial neural network and a Vector Support Engine (SVM) performed a systematic assessment of models through internal and external validation [24]. The researcher quantified the potential benefits of glucose prediction in reducing the frequency / duration of hypoglycemia [20]. For the patient with the type 1 diabetes (T1D) and insulin pump, the University of Ohio developed the intelligent decision based support system to treat these patients [21].Another important application of CGM sensors online is the generation of alerts when it is predicted that the glucose concentration is higher than the thresholds of the normal range [22].

To enhance the CGM sensor system performance following three area are identified: 1. improving the life span of the sensor system for hyper/hypoglycemic alert by predicting the future blood sugar concentration, 2. improving the precision of CGM data by eliminating the random noise component which overlapped to the glycemic signals, 3. improving the accuracy and eliminating the systemic error.

These three main challenges need to overcome by introducing the smart algorithm for CGM sensor systems which consists of following three modules (i) denoising; (ii) enhancement; and (iii) prediction. In this research more importance is given to the prediction module by using the Kriging prediction technique by using Matlab simulation. The daily activities of the patient is recorded by using smart phone application and blood glucose level is stored manually which are measured by using the smart sensor system. The recorded data is used to predict the blood glucose level of the monitored patient ahead and then compared with measured level. By using the measured and predicted levels the root mean square error(RMSE) is calculated to verify the algorithm and the results which are presented in the later part of this research work is very much reliable and give almost 95% accuracy.

3. CONTINUES GLUCOSE MONITORING (CGM)

In the beginning of the 21st century, CGM sensors have been developed by various companies but still it is very expensive for the common man and its life is also around 14 days. There two type of CGM sensors available which can be categorized as: implantable needle-type enzyme sensors, and systems based on the use of a micro-dialysis probe coupled with a glucose biosensor. A mobile based application is used to communicate with the CGM sensor by using Bluetooth connection to read and store the most recent measured blood glucose level to be used for in future for monitoring and treating the patient accurately.

4. KALMAN FILTER

In [25, 26], proposed Kalman filtering method in which past CGM data is used by supposing a double integrated random walk as prior for glucose dynamics. For the prediction and detection hypo-glycaemia, the authors in [26] used simulated data to explain the effect of measurement sapling intervals for prediction threshold. Statically, Kalman filter is a linear prediction model and algorithm which use series of measurement for long intervals which includes the statistical noise along with other factors

In [27] the approach was used on 13 time series relative to hypo-glycaemia clamps, in which glucose concentration was measured with the Medtronic CGMS sensor (sampling period of 5 min). Over all the dataset, the sensitivity and specificity of hypo-glycaemia (defined as glucose lower than70 mg/dL) prediction were calculated, for different PHs ranging from 5 to 30 min and different prediction thresholds, from 60 to 90 mg/dL, for hypo-glycaemia detection.

5. ALGORITHM TESTED FOR GLUCOSE MONITORING

The proposed algorithm is implemented by using the Matlab simulator along with the real time data collected from diabetes patients and following steps are key part of the research work.

Initially, existing prediction algorithm are studied thoroughly and their results are analyzed to make the opinion about the existing algorithms. Shortcomings in existing prediction algorithms for Blood Glucose are noted and try to be addressed in my proposed and tested prediction algorithm.

Prediction Methods	1st Prediction		5th Prediction		%Decrease at 10th	15th Prediction		% Decrease at 20th Prediction
	MSE $(K)^2$	RMSE (K)	MSE $(K)^2$	RMSE (K)		MSE $(K)^2$	RMSE (K)	
Kriging Predicto	**260**	**16.12**	**95**	**9.75**	**63.46**	**22**	**4.69**	**91.53**
Kalman Filter	**280**	**16.73**	**100**	**10**	**64.28**	**50**	**7.07**	**82.14**

The diabetes patient data is collected including blood glucose level, their doze, timing of doze, age of patient, age of diabetes and frequency of doze every day, etc.

After analyzing the collected data then existing algorithms are applied to predict the future blood glucose level of a particular patient for comparison purposes and results are presented in the later part of this research work. The Kriging based algorithm for prediction is applied the same patient data to predict future blood glucose level and is be compared to exiting algorithm and real time data.

In ordinary Kriging, a spatial phenomenon Z is assumed to be represented by its realizations $Z(t_1), Z(t_2). . . Z(t_n)$ at time $t_1, t_2. . . t_n$. Then the Kriging interpolator of Z at time t_0 is given below

$$\hat{Z}(t_0) = \sum_{i=1}^{n} \left(\lambda_i Z(t_i) \right),$$

where λ_i are the weights fulfilling the normalization condition, i.e., $\sum_{i=1}^{n}(\lambda_i) = 1$ and the expected error is $E[\hat{Z}(t_0) - Z(t_0)] = 0$ as used. The Kriging technique provides an optimal estimate in the sense that it minimizes the estimation variance and is unbiased as described by [12]. It can be shown that the optimal weights λ_i for the Kriging interpolator can be computed from the following system of linear equations as described by Curran and Atkinson (1998).

$$\Lambda = A^{-1} B,$$

$$\begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_n \end{pmatrix} = \begin{pmatrix} \gamma(t_1,t1)\ldots\ldots\gamma(t_1,t_n) \\ \vdots \\ \gamma(t_n,t_1)\ldots\ldots\gamma(t_n,t_n) \end{pmatrix}^{-1} \begin{pmatrix} \gamma(t_1,t^*) \\ \vdots \\ \gamma(t_n,t^*) \end{pmatrix},$$

where Λ is a vector comprising the weights, A is the spatial correlation matrix of sample with time difference $t_1, t_2, . . ., t_n$ and b is a vector whose elements represent the spatial correlation between t_0 and each t_i $\{ t_1, t_2, . . . , t_n \}$. All correlations are based on an appropriate variogram model defined for the spatial phenomenon under observation as described by [14]. By using the real time data Mean Square Error (MSE) is calculated to improve the prediction of Blood Glucose level.

Following technique is applied to calculate RMSE. To assess the performance of proposed algorithms for Blood Glucose level of particular patient, a root mean square error (RMSE) is used as performance metric. The MSE, defined as

$$\text{RMSE} = sqrt(\frac{1}{n}\sum_{i=1}^{n}(BG_i^t - BG_i^p)^2)$$

is used to characterize the accuracy of the Kriging process. Here BG_i^p is the current predicted Blood Glucose, BG_i^t is the true Blood Glucose level, n: is the number of predicted values per day.

6. Simulation Results and Discussion

For the purpose of the performance assessment of the algorithm, couple of the patient's real time blood sugar data is collected over the period of weeks at different time of the day with regular intervals of 30 minutes. After each measurement of the real time blood glucose level of the patient and it is integrated with existing data, then following algorithm is applied by using Matlab simulator.

To check the performance of the Kriging based algorithm and for the comparison purpose Kalman filter is also used to predict the blood glucose level. From the results below we can deduce that performance of the Kriging algorithm is better than Kalman filter. Kriging based algorithm learn quickly as compared to Kalman filter.

Procedure Measure the blood sugar level

1- Train the predictor to predict next values

2- Measure again and integrate with existing data for prediction

for:

3- Take measurement for all ($\{b_1, b_2, \cdots, b_m\}$)

4- Set *loops* = 0; Set *MaxLoops* =MAX LOOPS;

5-Accept & integrate for all ($\{b_1, b_2, \cdots, b_m\}$)

6- Predict Blood sugar 30 minutes ahead

7- Measure blood sugar level

8- Calculate RMSE

$$\mathrm{RMSE} = sqrt(\frac{1}{\mathrm{n}}\sum_{i=1}^{n}(BG_{\mathrm{i}}^{\mathrm{t}} - \mathrm{BG}_{\mathrm{i}}^{\mathrm{p}})^2)$$

9- End; Stop;

Figure 5 below shows the plotted results of the patient one with real time data and predicted data. As in Initial stages the both predictor was in learning phase and predicted results have root mean square error (RMSE) as compared with later stages. Kriging based algorithm learn quickly as compared to Kalman filter, the performance of the Kriging predictor is better than the Kalman filter.

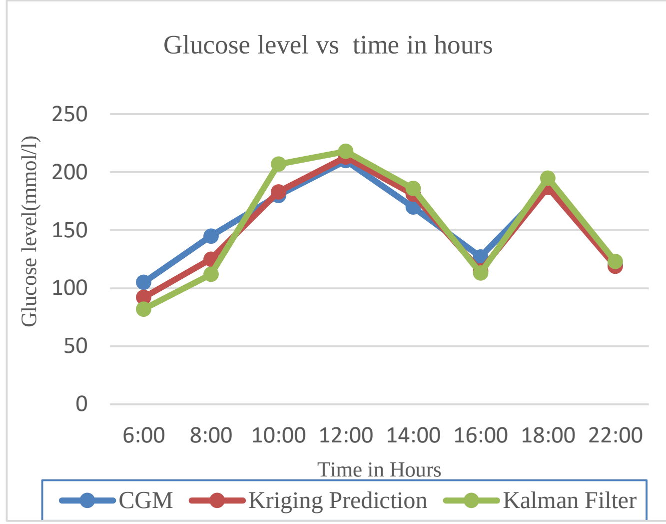

Figure 5: Measured glucose vs predicted

In Figure 6 below root mean square error is plotted for both predictors. RMSE is calculated by using the real time values vs the predicted value by the Kriging and Kalman filter predictor. It shows that Kriging algorithm learn quickly as compared to Kalman filter, as Kriging predictor predict closer value to the real time glucose level. By using more data for the predictor, it shows at the end the root mean square error is very small as compared to initial stage.

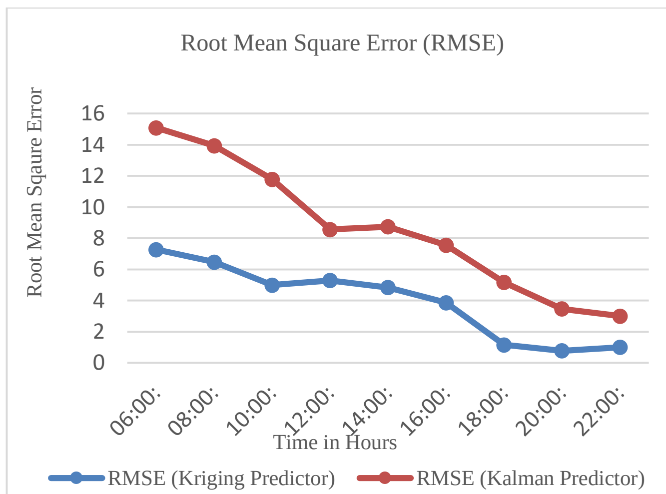

Figure 6: Mean square error of different prediction models

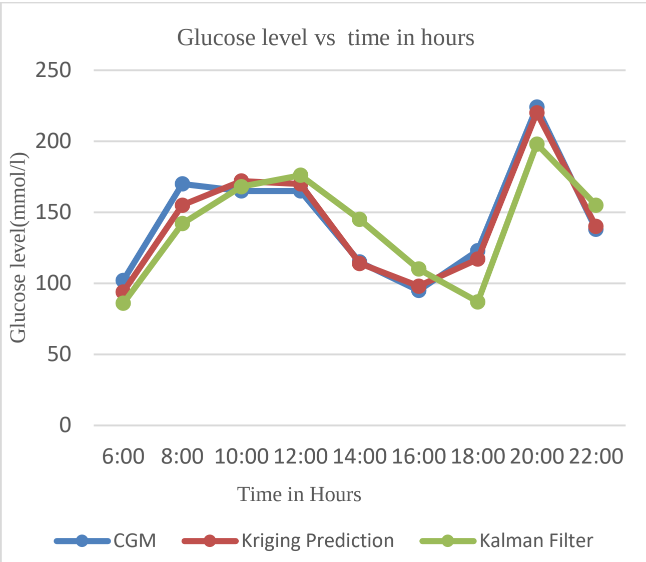

Figure 7: Measured glucose vs predicted

Figure 7 above shows the results of the prediction and real time data of second patient, from above results we can conclude that Kriging prediction learn quickly and predict glucose level closer to real time glucose level measured by using CGM sensor.

Figure 8 below shows the calculated mean square error and root mean square error for 2nd patient and it shows that Kriging prediction technique is performing very well in terms of the producing error for the next values to be predicted.

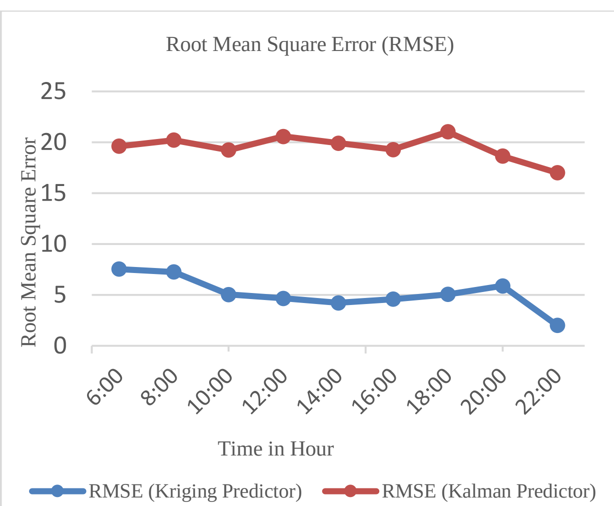

Figure 8: Mean square error of different prediction models

7. Conclusion

Diabetic patients are mainly use CGM system for continues monitoring their real time glucose level which currently very expensive. CGM system generate the hypo and hyperglycemic alerts and based on the alert the patient takes the dose of insulin to maintain the blood glucose level. The proposed prediction algorithm for the blood glucose monitoring can be highly used in emergency situation as it can monitor blood glucose level continually by using prediction. The initial results are very optimal and very much encouraging, there are other aspects that need to be studied. The proposed system comprised on the two steps, in first step real time glucose level is measured and stored in the database which is used in second step for prediction by using the Kriging algorithm. By using Kriging interpolation the predicted results are very encouraging as much as up to 90% accuracy as compared to other prediction methodologies. Lastly, the prediction module allows the prediction based to forecast hypo and hyperglycemic events by an average of 30 minutes before it occur.

The results presented above are very encouraging by using the optimal based prediction algorithms, there are other aspects that need to be studied in future. In future the IoT device can be combined with the cloud computing so that the database can be shared in all the hospitals for the intensive care and treatment for corresponding patient.

Acknowledgement:

This work is part of the research study titled "Un- Interrupted Glucose Monitoring and Prediction by Using Smart Sensor System "supported by Deanship of Research, Islamic University of Madinah, Almadinah Alunwarah, Kingdom of Saudi Arabia.

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