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Linear Prediction System in Measuring Glucose Level in Blood

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***Abstract*—**Diabetes is a medical condition that can lead to various diseases such as stroke, heart disease, blindness and obesity. In clinical practice, the concern of the diabetic patients towards the blood glucose examination is rather alarming as some of the individual describing it as something painful with pinprick and pinch. As for some patient with high level of glucose level, pricking the fingers multiple times a day with the conventional glucose meter for close monitoring can be tiresome, time consuming and painful. With these concerns, several non-invasive techniques were used by researchers in measuring the glucose level in blood, including ultrasonic sensor implementation, multisensory systems, absorbance of transmittance, bio-impedance, voltage intensity, and thermography. This paper is discussing the application of the near-infrared (NIR) spectroscopy as a non-invasive method in measuring the glucose level and the implementation of the linear system identification model in predicting the output data for the NIR measurement. In this study, the wavelengths considered are at the 1450 nm and 1950 nm. Both of these wavelengths showed the most reliable information on the glucose presence in blood. Then, the linear Autoregressive Moving Average Exogenous model (ARMAX) model with both un-regularized and regularized methods was implemented in predicting the output result for the NIR measurement in order to investigate the practicality of the linear system in this study. However, the result showed only 50.11% accuracy obtained from the system which is far from the satisfying results that should be obtained.

***Keywords*—**Diabetes, glucose level, linear, near-infrared (NIR), non-invasive, prediction system.

I. Introduction

KNOWN as the central carbohydrate, glucose derived from the Greek word “glykys”, meaning “sweet”, with two optical isomers, D-glucose and L-glucose [1]. For human body, glucose is very important, and frequent blood-glucose sensing is important for diabetic patients to maintain their glucose level in the normal clinical range (3.5–6.1 mmol/L) [2]. However, the diabetes disease can occur with the poor management of dietary of individual. About 347 million people suffered from diabetes in 2004, and an estimated 3.4 million patients died from consequences of high blood sugar [3].

Some of the references cited that the blood-glucose level is in the range of [4]:

$$Diabetic = \begin{cases} 0, & 4\ mmol/L \leq BGL \leq 7\ mmol/L \\ 1, & BGL > 7\ mmol/L \end{cases} \quad (1)$$

where, 0 = person without diabetic, 1 = person with possible diabetic

For patients in a serious condition, continuous diabetes management or monitoring are essential. If the glucose level exceeds this level, the person is almost certainly suffering from diabetes. Continuous diabetes management may help in maintaining the sugar level in the acceptable range for the human body and it is essential to ensure that the patient does not develop the severe conditions induced by a high sugar level in the blood. Other health complications such as kidney failure, heart disease, and stroke may occur in the long term if it is not properly controlled [5].

Estimated, 347 million people suffered from diabetes in 2004, and around 3.4 million patients died from consequences of high blood sugar [13]. In many cases, the diabetes patients expressed their concerns towards the blood glucose examination and describing it as something painful with pinprick and pinch. The continuous monitoring towards the critical patients, involving pricking the fingers multiple times a day can be tiresome and painful. The process also difficult for the patients whose diagnose with dexterity limitation, aglophobia or with the anxiety problem. Frequent monitoring for diabetic patients, especially for those with a severe and serious condition, is a must as it is an incurable disease with a life-threatening metabolic disorder [6].

II. Methodology

This study flows consist of data acquisition both using the conventional glucose meter as the reference device and the NIR spectroscopy as the input data device. The input data were analyzed using the linear system identification model which is the ARMAX, to investigate the effectiveness of the linear model in predicting the glucose level in blood using the NIR wavelength. The dataset went through the pre-processing stage to enhance the feature of the input data set.

III. Data Acquisition

The data collected from three groups which are the patients who were diagnosed with diabetic, the non-diabetic individuals and a control group without early diagnose and the process conducted under supervision of the personnel at Outpatient Department (OPD), Hospital Universiti Sains Malaysia (HUSM) Kubang Kerian, Kelantan, Malaysia.

The human fingertips are among the best position to be measured besides the earlobe. This is because the skin of the

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fingertips is much thinner and contains more blood vessels which are observable. The dataset contains 135 sets of data obtains from the three groups of subjects. The data taken from the subjects are varying in terms of gender, age, race or their medical condition (critical or not critical). The study on the subjects has to be performed in accordance to ethical principles of the Good Clinical Practice and the Declaration of Helsinki [7], [8]. Fig. 1 shows the illustrated setup of the NIR spectrometer during the data measurement.

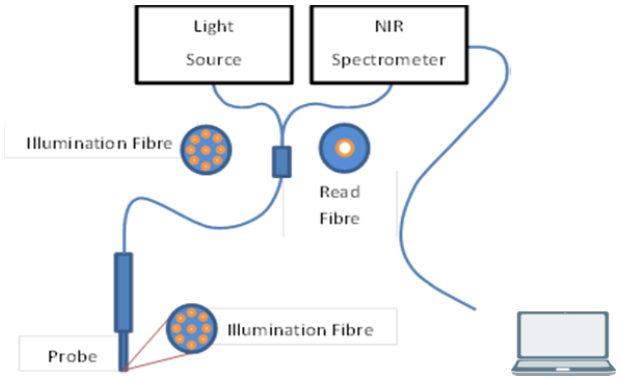


Fig. 1 The illustration of the NIR spectroscopy instrument

IV. Data Pre-Processing

For this research, the data pre-processing methods used are noise filtering, data sampling, interval correction and data distribution process. The Savitzky - Golay filter used to filter the wavelength, removing any unwanted information from the data set. The data sampling process extracted the wavelength with only the useful information to be fed as the input data set. Then, the data interval correction process is applied to selected peaks in the NIR spectrum. The data distribution process then implemented to divide the data into the training, testing and validation data set randomly. Fig. 2 shows the flow of the data pre-processing stage.

V. System Identification

In this study, the linear model used is the ARMAX model. ARMAX model is defined as:

$$G(z,p) = \frac{B(z)}{A(z)}, H(z,p) = \frac{1}{A(z)} \quad (2)$$

where, $A(z) = 1 + a_1 z^{-1} + \cdots + a_{n_a} z^{-n_a}, B(z) = b_1 z^{-1} + \cdots + b_{n_b} z^{-n_b} G(p,z)$ and $H(p,z)$are filters of finite order and functions of a parameter vector p,

$$p = [a_1 \ldots . a_{n_a} \ b_1 \ldots . b_{n_b}]^T \quad (3)$$

The un-regularized and regularized ARMAX models are both implemented to determine the optimum testing result of the system.

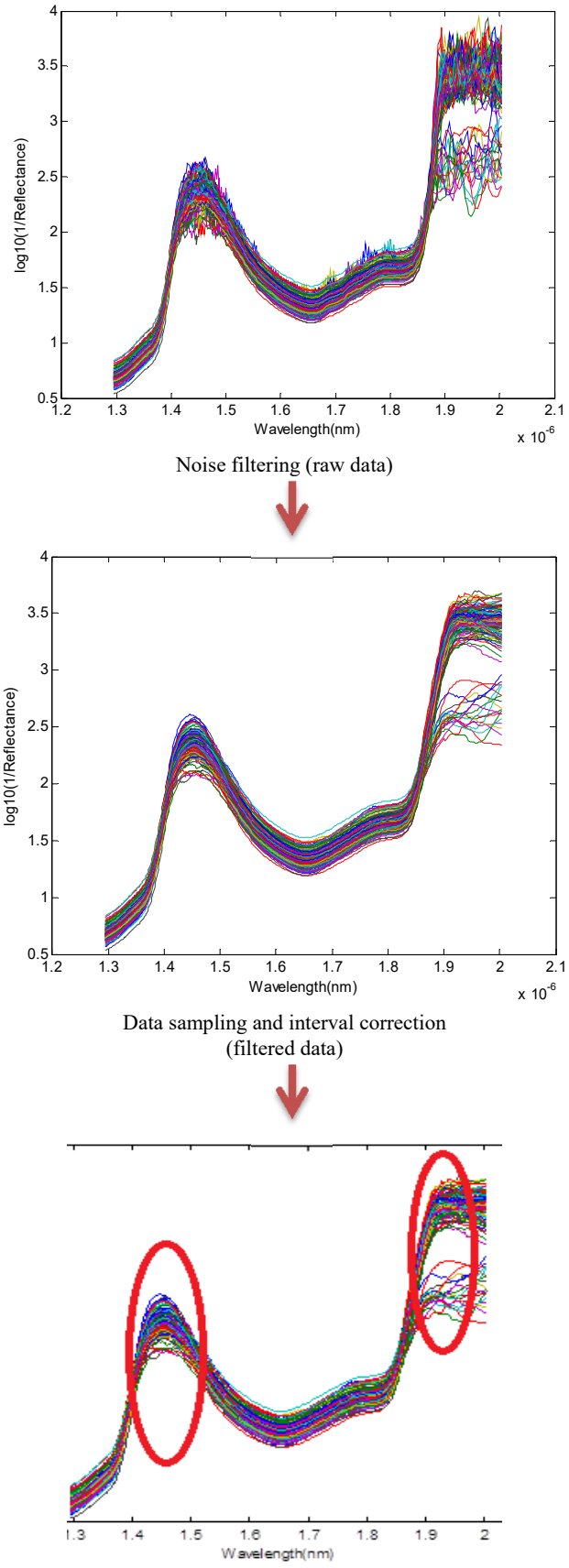


Fig. 2 The flows of data pre-processing

VI. Model Validation

The Clarke Error Grid Analysis is widely used as a reference to quantify the clinical accuracy of patient estimates of the glucose levels in blood with the conventional invasive method [5], [9]-[11]. This method used to validate the linear system identification model which is implemented in this research. The data from output set and reference set are plotted to determine the region of distribution [12].

Region A: within 20% of the reference sensor (clinically accurate).

Region B: outside of 20% but would not lead to an inappropriate treatment (clinically acceptable).

Region C: leading to unnecessary treatment (overcorrection).

Region D: indicating a potentially dangerous failure to detect hypoglycaemia or yperglycaemia (dangerous failure to detect).

Region E: confuse treatment of hypoglycaemia for hyperglycaemia and vice versa (serious error).

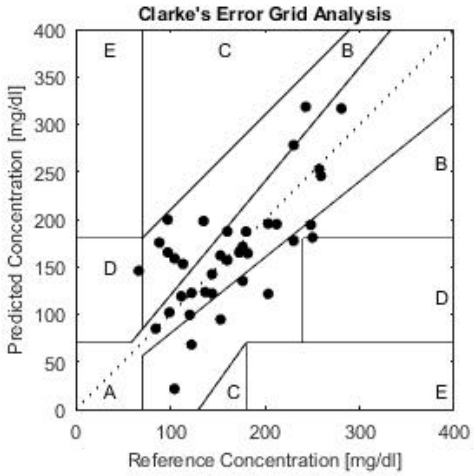
VII. Result

The prediction result of the ARMAX model in Table I shows only 47.79% for un-regularized model and 50.11% for regularized model which are far from the satisfying results that should be obtained.

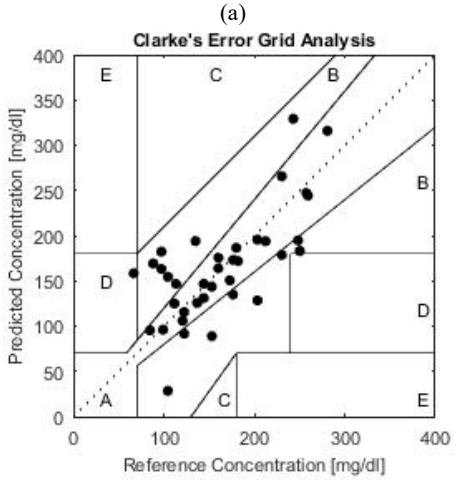
TABLE I
The Un-Regularized and Regularized for Training and Testing Result

Filter Length	UNREGULARIZED						REGULARIZED					
	Training			Testing			Training			Testing		
	R	R^2	%	R	R^2	%	R	R^2	%	R	R^2	%
5	0.88	0.77	76.70	0.70	0.49	48.93	0.88	0.77	76.95	0.71	0.50	50.24
7	0.88	0.77	77.14	0.71	0.50	49.98	0.87	0.76	76.46	0.71	0.51	50.52
9	0.87	0.76	75.85	0.69	0.48	47.51	0.87	0.75	75.36	0.69	0.48	47.55
11	0.88	0.77	76.90	0.70	0.48	48.50	0.86	0.74	74.49	0.69	0.48	48.22
13	0.86	0.74	74.25	0.69	0.48	47.51	0.86	0.74	73.94	0.68	0.47	46.83
15	0.86	0.75	74.75	0.68	0.47	46.62	0.86	0.74	73.94	0.69	0.47	47.32
17	0.86	0.74	73.65	0.69	0.47	47.03	0.86	0.74	73.70	0.70	0.49	48.72
19	0.86	0.74	74.06	0.69	0.47	47.42	0.86	0.74	73.99	0.70	0.49	48.65
21	0.86	0.74	74.18	0.69	0.47	46.95	0.87	0.75	74.82	0.70	0.49	48.54
23	0.86	0.74	73.96	0.67	0.45	45.36	0.87	0.75	74.89	0.69	0.47	46.95
25	0.86	0.74	74.20	0.67	0.45	45.33	0.87	0.75	75.10	0.69	0.47	47.18
27	0.87	0.76	75.78	0.68	0.47	46.64	0.87	0.76	76.02	0.70	0.49	48.69
29	0.87	0.76	76.02	0.69	0.48	47.67	0.88	0.77	76.67	0.71	0.50	50.01
31	0.88	0.77	76.70	0.69	0.48	48.09	0.88	0.77	77.11	0.71	0.50	49.86
33	0.87	0.77	76.55	0.69	0.48	47.79	0.88	0.77	76.65	0.71	0.50	50.11

The training and testing result with filter length 33 picked as the optimum value obtained which are from the modeling stage. The result from the Clarke Grid Error likewise is unsatisfying as shown in Fig. 3. From the figure, only 54.05% output data scattered in Region A for un-regularized model in (a), and 56.76% data scattered in Region A for regularized model in (b).



(a)



(b)

Fig. 3 (a) The scattering of the un-regularized testing data (b) The scattering of the regularized testing data

VIII. Conclusion

The implementation of the linear system identification model is discussed in this paper, however resulting in the

ineffectiveness of the ARMAX model in predicting the output value of the NIR spectrum. The possible cause of the unsatisfying result is because of the influence from environmental and physiology factors during NIR measurement such as the human body and ambiance temperature or humidity, and also the patients' skin color and textures. The implementation of the nonlinear models is proposed in future work to broaden the investigating parameter in order to improve the prediction result.

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