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Research Article

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Predicted Fasting Plasma Glucose Values during the COVID Period, using the pre-COVID data as Baseline, Applying the Higher Order Equations of Interpolation Perturbation Theory from Quantum Mechanics and Weight as the Perturbation Factor based on GH-Method: Math-Physical Medicine (No. 463)

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Abstract

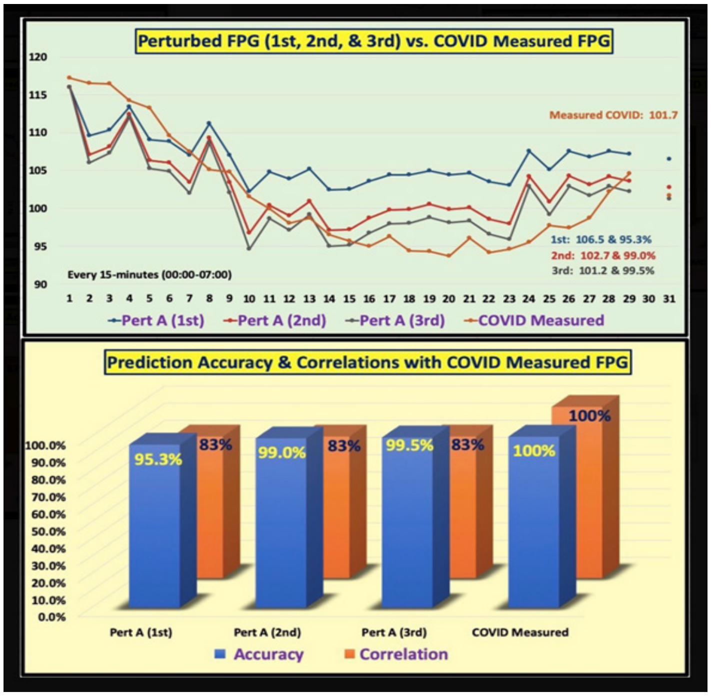
In this research note, the author applies the methodology of higher-order interpolation perturbation theory from quantum mechanics on his medical research work. This perturbation theory application includes the first-order, second-order, and third-order, to generate three predicted postprandial plasma glucose (PPG) waveforms with different prediction accuracies. He then collects two separate measured fasting plasma glucose (FPG) data and their synthesized waveforms generated for two periods, pre-COVID (5/5/2018 - 1/18/2020) and COVID (1/19/2020 - 6/7/2021), as his two baselines for comparison between 3 predicted FPG data and waveforms (using pre-COVID as the baseline) and the measured COVID FPG data and waveform.

There are two final yardsticks to check in this study. The first target is to verify the prediction accuracies of these three perturbed FPG values. The second target is to examine the waveform similarity via calculated correlation coefficients between the measured FPG dataset or waveform and the three perturbed FPG datasets or waveforms.

The main purpose is to examine the prediction accuracy and waveform similarities of his current or future period's glucoses by using three different orders of perturbation equations based on the glucose data from the previous period as the prediction baseline.

In summary, the obvious conclusion drawn from this research work is that the perturbation equation provides a predicted FPG with high accuracy and almost duplicative waveform shapes. As a matter of fact, the higher-order of the perturbation equation used, the better results can be achieved for prediction accuracy. In this study, the first-order perturbation offers 95.3% prediction accuracy, the second-order perturbation provides 99.0% prediction accuracy, and the third-order perturbation delivers 99.5% prediction accuracy. All three perturbed PPG wave forms have equal level of waveform shape similarity with 83% versus the measured COVID FPG waveform. The lower than 90+% correlations are due to the selection of the pre-COVID FPG data as his calculation baseline.

In the real world, there are very few diabetes doctors and patients who can understand the perturbation theory of quantum mechanics, let alone be able to apply this theory on calculation of predicted future glucose based on previous data with a desired high prediction accuracy.



Introduction

In this research note, the author applies the methodology of higher-order interpolation perturbation theory from quantum mechanics on his medical research work. This perturbation theory application includes the first-order, second-order, and third-order, to generate three predicted postprandial plasma glucose (PPG) waveforms with different prediction accuracies. He then collects two separate measured fasting plasma glucose (FPG) data and their synthesized waveforms generated for two periods, pre-COVID (5/5/2018 - 1/18/2020) and COVID (1/19/2020 - 6/7/2021), as his two baselines for comparison between 3 predicted FPG data and waveforms (using pre-COVID as the baseline) and the measured COVID FPG data and waveform.

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Methods

The author has chosen not to repeat all of the details regarding his applied methods as described in other papers. Instead, he outlines a few important equations, formulas, or conditions in this article.

MPM Background

To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from the published 400+ medical papers.

The first paper, No. 386 (Reference 1) describes his MPM methodology in a general conceptual format. The second paper, No. 387 (Reference 2) outlines the history of his personalized diabetes research, various application tools, and the differences between biochemical medicine (BCM) approach versus the MPM approach. The third paper, No. 397 (Reference 3) depicts a general flow diagram containing ~10 key MPM research methods and different tools.

Higher-Order Interpolation Perturbation Theory

The author applies the higher-order interpolation perturbation method to obtain his three "perturbed PPG" waveforms based on one function of the selected carbs/sugar intake amount functioning as the ***perturbation factors***, which is the "Slope Equation". He uses the "measured PPG" waveform as his "reference waveform".

The following polynomial function is used as the perturbation equation:

$$A = f(x)$$
$$= A0 + (A1*x) + (A2*x**2)+(A3*x**3) + ... + (An*x**n)$$

Where A is the perturbed glucose, Ai is the measured glucose, and ***x is the "perturbation factor"*** *based on different carbs/sugar intake amounts.*

For this particular study, he choose his ***Ai where i=1 to 3.*** Therefore, the perturbation theory equation from above can be simplified to the following form:

$$A = f(x)$$
$$= A0 + (A1*x) + (A2*x**2)+(A3*x**3)$$

Or the third-order interpolation perturbation equation can then be expressed in the following general format:

Y i
= Y1 + (slope 1) * (Y2 - Y1) +
(slope 2) * (Y2-Y1) + (slope*3) * (Y2-Y1)

More specifically, the following formats of three perturbation equations are utilized in his calculations:

Y of first order
= (Y2-Y1)*(slope 1)

Y of second order
= (Y2-Y1)*(slope 1+slope 2)

Y of third order
= (Y2-Y1)*(slope 1+slope 2+slop 3)

Where:
Y1 = original glucose Y at time 1
Y2 = advanced glucose Y at time 2
(Y2-Y1) = (Glucose Y at Time 2 - Glucose Y at Time 1)

The perturbation factor of ***Slope*** is an arbitrarily selected parameter that controls the size of the perturbation. The author has chosen a function of his weight (lbs.), as the perturbation factor or slope, which is further defined as follows:

Slope 1
= (Selected Weight - Low-bound Weight) / (High-bound Weight - Low-bound Weight)

Slope 2
= (Slope 1 * Slope 1)
or (Slope**2)

Slope 3
= (Slope 1 * Slope 1 * Slope 1)
or (Slope**3)

It should be noted that, for achieving a better predicted glucose value, ***the selected weight amount should be within the range of the high-bound weight and the low-bound weight.***

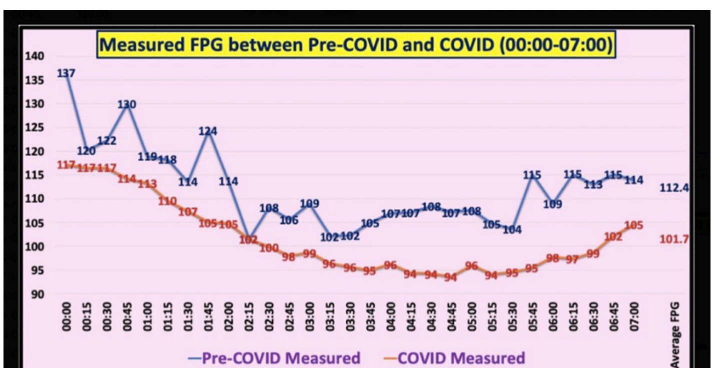
In this particular study, he selects the 165.8 lbs. as the low-bound weight and 175.3 lbs. as the high-bound weight, while 169.6 lbs. as his selected weight amount.

Therefore, in this particular study, his three slope values are calculated as follows:

Slope 1 = 0.40
Slope 2 = 0.16
Slope 3 = 0.06

Results

Figure 1 shows the tight relationship between FPG and body weight. This can be demonstrated via a high correlation coefficient of 83%, during a longer period from 1/1/2014 to 6/9/202, and another high correlation coefficient of 67%, during a shorter period from 5/5/2018 to 6/9/2121. Based on these two considerable high correlation coefficients, the author decided to use the body weight amount as the perturbation factor for the predicted FPG analysis, during the COVID period (1/19/2020 - 6/9/2021), while using the FPG data from the pre-COVID period (5/5/2018 - 1/18/2020) as his baseline of calculations.



Average FPG	112.4	101.7		106.5	102.7	101.2	101.7	91%
FPG	Pre-COVID Measured	COVID Measured	FPG	Pert A (1st)	Pert A (2nd)	Pert A (3rd)	COVID Measured	Conversion %
Prediction Accuracy			Accuracy	95.3%	99.0%	99.5%	100%	Conversion Factor
Correlation			Correlation	83%	83%	83%	100%	85%
Weight in the morning	High-Weight	Selected-Weight	Low-Weight					
Selection of Carbs	175.3	169.6	165.8					
Perturbation Theory: Slope	1st order	2nd order	3rd order					
(Select-Low)/(High-Low)	0.40	0.16	0.06					

Figure 1: Tight relationship between FPG and Weight for the longer period of R=83% and the shorter period of R=67%

Figure 2 illustrates two FPG waveforms for the pre-COVID period (5/5/2018 - 1/18/2020) and COVID period (1/19/2020 - 6/7/2021), with associated perturbation analysis results. We should pay attention to certain key data and curve characteristics of these two FPG waveforms which are described below.

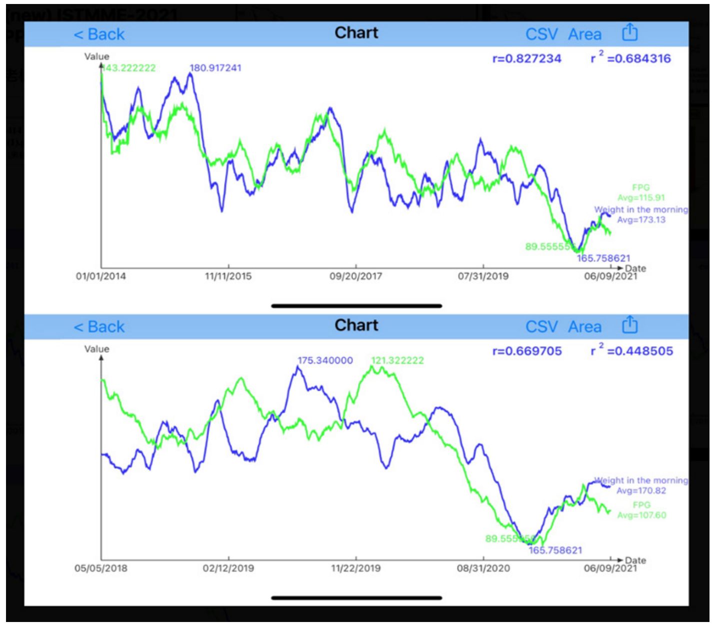


Figure 2: Two FPG waveforms for both Pre-COVID period (5/5/2018 - 1/18/2020) and COVID period (1/19/2020 - 6/7/2021), with associated perturbation analysis results

The average FPG is 112 mg/dL for the pre-COVID period and 102 mg/dL for the COVID period with a difference of 10 mg/dL. Moreover, the pre-COVID FPG curve has more zig-zags in its waveform while the COVID FPG curve is relatively smoother.

Figure 3 assembles three Perturbed FPG curves and one measured FPG curve for the COVID period (1/19/2020 - 6/7/2021) using the pre-COVID FPG data as its baseline dataset and body weight as the perturbation factor. It should be pointed out that the 3 perturbed FPG curves utilize the pre-COVID data as their baseline; therefore, they possess the similar zig-zag characteristics in their FPG waveforms.

It is worth mentioning again that he has chosen the selected weight of 169.6 lbs. which is remarkably close to his actual measured average weight of 169.5 lbs. in the COVID period. It is also located approximately at the midpoint (170.6 lbs.) of his low-bound weight of 165.8 lbs. and high-bound carbs of 175.3 lbs. His three calculated perturbation slopes are 0.40 for the first-order perturbation, 0.16 for the second-order perturbation, and 0.06 for the third-order perturbation.

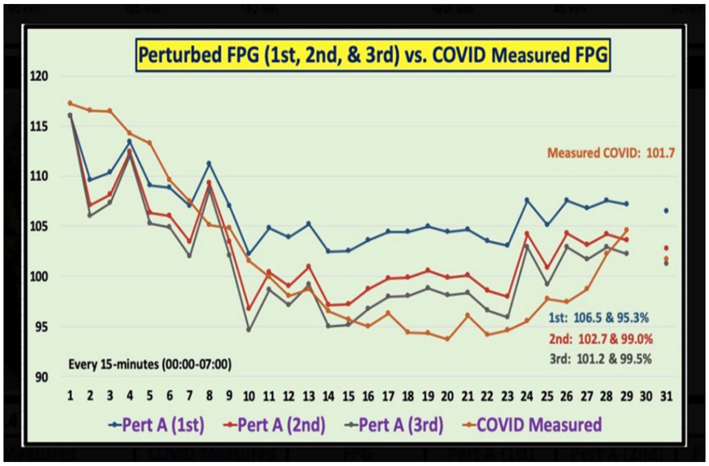


Figure 3: Three Perturbed FPG curves and one measured FPG curve for the COVID period (1/19/2020 - 6/7/2021) using pre-COVID FPG data as its baseline dataset and body weight as its perturbation factor

In Figure 4, the bar diagram illustrates the three prediction accuracies and three correlation coefficients for the 3 perturbed FPG in the COVID period (using pre-COVID measured data as their baselines) versus the measured FPG of the COVID period

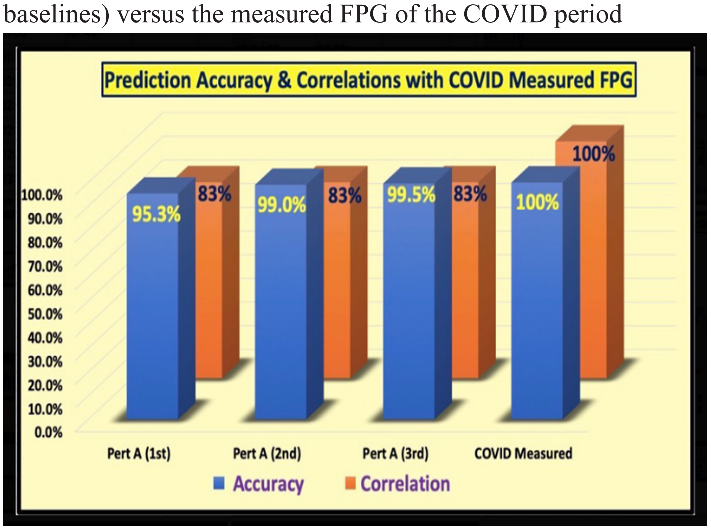


Figure 4: Prediction accuracies and correlation coefficients of 3 perturbed FPG in COVID period (using pre-COVID measured data as their baselines) versus the measured FPG of COVID period

The average FPG value and prediction accuracy of each perturbation equation for the COVID period are listed below:

Measured: 101.7mg/dL, 100%
First-order: 106.5 mg/dL, 95.3%
Second-order:102.7 mg/dL, 99.0%
Third-order: 101.2 mg/dL, 99.5%

All three perturbed waveform predictions have the same shape similarity (i.e., same correlation coefficients of R=83%) in comparison against the measured COVID FPG. These slightly lower than 90% of R is due to the fact that the 3 predicted COVID waveforms uses the pre-COVID measured data as their baseline of calculation. Nevertheless, an 83% correlation is still considered as an extremely high number in terms of waveform shape similarity comparison.

The mathematical power of achieving excellent approximation of PPG values and their corresponding waveforms by utilizing the perturbation theory can be observed clearly via the summarized table shown below in the format of first-order, second-order, and third-order:

Correlation: 83%, 83%, 83%
Accuracy: 95.3%, 99.0%, 99.5%

Conclusions

In summary, the obvious conclusion drawn from this research work is that the perturbation equation provides a predicted FPG with high accuracy and almost duplicative waveform shapes. As a matter of fact, the higher-order of the perturbation equation used, the better results can be achieved for prediction accuracy. In this study, the first-order perturbation offers 95.3% prediction accuracy, the second-order perturbation provides 99.0% prediction accuracy, and the third-order perturbation delivers 99.5% prediction accuracy. All three perturbed PPG wave forms have equal level of waveform shape similarity with 83% versus the measured COVID FPG waveform. The lower than 90+% correlations are due to the selection of the pre-COVID FPG data as his calculation baseline.

In the real world, there are very few diabetes doctors and patients who can understand the perturbation theory of quantum mechanics, let alone be able to apply this theory on calculation of predicted future glucose based on previous data with a desired high prediction accuracy [1-38].

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