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Research Article

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Predict PPG Values of COVID Period (using the pre-COVID data as the baseline) Applying the Higher Order Equations of Interpolation Perturbation Theory from Quantum Mechanics and Carbs/Sugar Intake Amount as the Perturbation Factor Based on GH-Method: Math-Physical Medicine (No. 462)

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Abstract

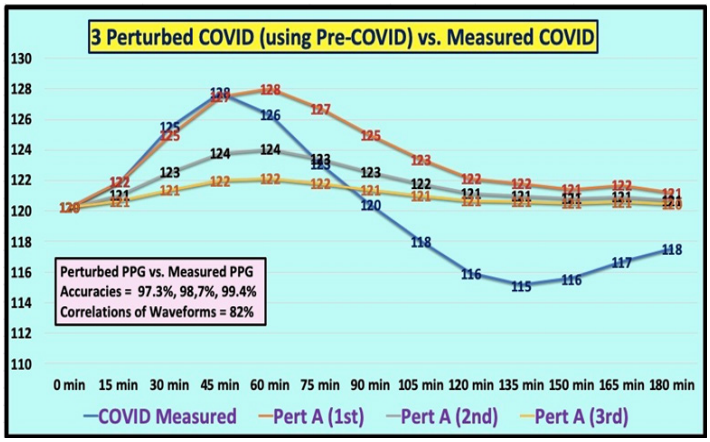
In this research note, the author applies the methodology of higher-order interpolation perturbation theory from quantum mechanics on his medical research work. This perturbation theory application includes the first-order, second-order, and third-order, to generate three predicted PPG waveforms with different prediction accuracies. He then collects two separate measured postprandial plasma glucose (PPG) 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 two baselines for comparison between predicted PPG data and waveforms (using pre-COVID as the baseline) and the measured COVID PPG 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 PPG values. The second target is to examine the waveform similarity via calculated correlation coefficients between the measured PPG dataset or waveform and the three perturbed PPG datasets or waveforms.

The main purpose is to examine the prediction accuracy and waveform similarities in his current or future period of 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 PPG with high accuracy and 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 97.3% prediction accuracy, the second-order perturbation provides 98.7% prediction accuracy, and the third-order perturbation delivers 99.4% prediction accuracy. All three perturbed PPG waveforms have equal level of waveform shape similarity with 81% versus the measured COVID PPG waveform. The lower than 90+% correlations are due to the selection of the pre-COVID PPG 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 PPG waveforms with different prediction accuracies. He then collects two separate measured postprandial plasma glucose (PPG) 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 two baselines for comparison between predicted PPG data and waveforms (using pre-COVID as the baseline) and the measured COVID PPG 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, that 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 the calculations of this study:

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

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

Y of third order = (Y2-Y1)*(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 carbs/sugar intake amount, as his perturbation factor or slope, which is further defined as follows:*

In this particular study, he selects the 4.9 grams as his low-bound carbs/sugar and 21.8 grams as his high-bound carbs/sugar, while 13.2 grams as his selected carbs/sugar amount.

The equations for 3 slopes are:
Slope 1
= (Selected Carbs - Low-bound Carbs) / (High-bound Carbs - Low-bound Carbs)

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 carbs amount should be within the range of the high-bound carbs and the low-bound carbs, where these two boundary carbs amounts should be within 4x in magnitude to each other.

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

Slope 1 = 0.53

Slope 2 = 0.28
Slope 3 = 0.15

Results

Figure 1 shows the background information of PPG for both pre-COVID period and COVID period.

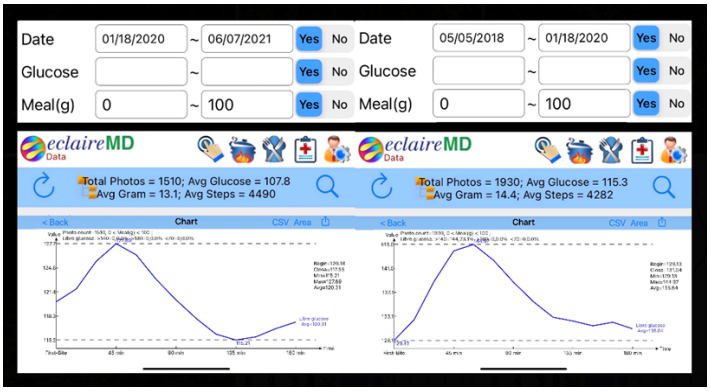
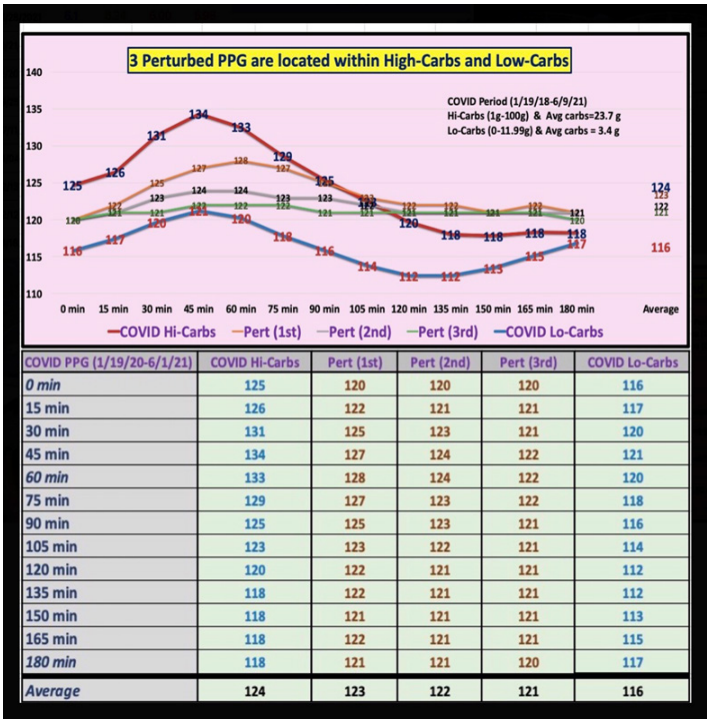


Figure 1: Two baseline periods of Pre-COVID (5/5/2018 - 1/18/2020) and COVID (1/19/2020 - 6/7/2021)

Figure 2 reflects his input data and valuation results of this study.



COVID PPG (1/19/20-6/1/21)	COVID Hi-Carbs	Pert (1st)	Pert (2nd)	Pert (3rd)	COVID Lo-Carbs
0 min	125	120	120	120	116
15 min	126	122	121	121	117
30 min	131	125	123	121	120
45 min	134	127	124	122	121
60 min	133	128	124	122	120
75 min	129	127	123	122	118
90 min	125	125	123	121	116
105 min	123	123	122	121	114
120 min	120	122	121	121	112
135 min	118	122	121	121	112
150 min	118	121	121	121	113
165 min	118	122	121	121	115
180 min	118	121	121	120	117
Average	124	123	122	121	116

Figure 2: 3 Perturbed PPG curves and 1 measured PPG curve for both pre-COVID period (5/5/2018 - 1/18/2020) and COVID period (1/19/2020 - 6/7/2021)

In Figures 1 and 2, we should pay attention to certain key data and curve characteristics of these two PPG waveforms which are described below.

The peak PPG values around 45-minutes to 60-minutes are 145 mg/dL for the pre-COVID period and 128 mg/dL for the COVID period. The pre-COVID PPG waveform is gradually declining after 75-minutes all the way to 180-minutes, but the COVID PPG waveform has a curve tilting-upward point at 135-minutes.

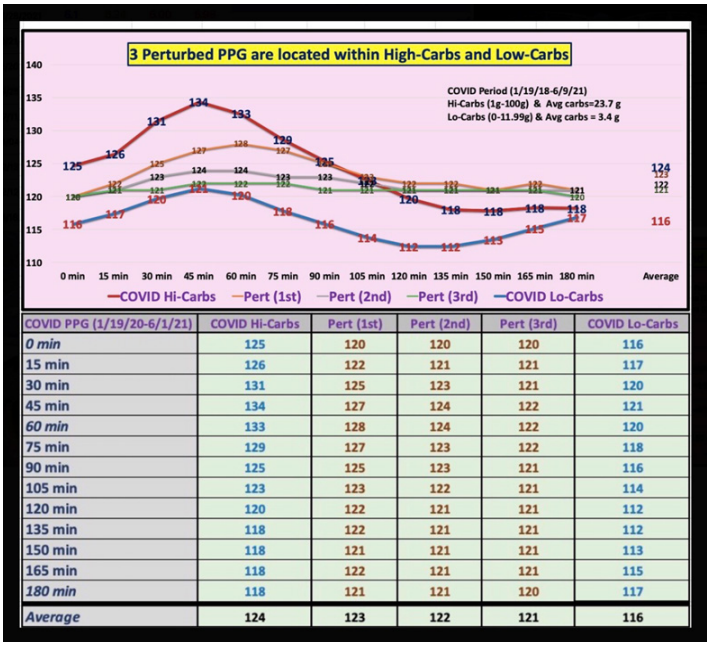
Figure 3 assembles the pre-COVID and COVID PPG waveforms into one graphic diagram. Therefore, the different peak values as well as the waveform tilting upward at 135-minutes of the COVID period are clearly observed. The author conducted three different orders of perturbation for both periods using each period's measured PPG data as their baseline data. Therefore, both periods have demonstrated extremely high prediction accuracies (>99.8%) and waveform shape similarities (>90.0%).

(PPG (1/19/20-6/1/21)	COVID Measured	Pert A (1st)	Pert A (2nd)	Pert A (3rd)	Pre-COVID Measured
0 min	120	120	120	120	129
15 min	122	122	121	121	133
30 min	125	125	123	121	139
45 min	128	127	124	122	144
60 min	126	128	124	122	145
75 min	123	127	123	122	142
90 min	120	125	123	121	139
105 min	118	123	122	121	136
120 min	116	122	121	121	133
135 min	115	122	121	121	132
150 min	116	121	121	121	132
165 min	117	122	121	121	132
180 min	118	121	121	120	131
Average	120.3	123.5	121.8	121.0	135.8
Prediction Accuracy	*Perturbed vs. COVID Measured*	*97.3%*	*98.7%*	*99.4%*	
Correlation	*Perturbed vs. COVID Measured*	*81%*	*81%*	*81%*	
Carbs & Walking	*High-carbs*	*Selected-total*	*Low-carbs*	*Conversion Factor*	
Selection of Carbs	*21.8*	*13.2*	*4.9*	*0.93*	
Perturbation Theory		*1st order*	*2nd order*	*3rd order*	
(Select-Low)/(High-Low)	*Slope*	*0.49*	*0.24*	*0.12*	

Figure 3: Table of input data and calculation results of 3 perturbed PPG (using pre-COVID measured data as their baselines) versus the measured PPG of COVID period

It should be noted again that he has chosen the selected carbs of 13.2 grams, which is his actual measured carbs/sugar amount in the COVID period, located approximately in the middle point of the low-bound carbs of 4.9 grams and high-bound carbs of 21.8 grams. His three calculated slopes are 0.53 for the first-order perturbation, 0.28 for the second-order perturbation, and 0.15 for the third-order perturbation.

Figure 4 depicts the ending result of the COVID predicted PPG using the pre-COVID data as his calculation baseline.



COVID PPG (1/19/20-6/1/21)	COVID Hi-Carbs	Pert (1st)	Pert (2nd)	Pert (3rd)	COVID Lo-Carbs
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75 min	129	127	123	122	118
90 min	125	125	123	121	116
105 min	123	123	122	121	114
120 min	120	122	121	121	112
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150 min	118	121	121	121	113
165 min	118	122	121	121	115
180 min	118	121	121	120	117
Average	124	123	122	121	116

Figure 4: Comparison of 3 perturbed PPG waveforms (using the pre-COVID measured data as their baselines) versus the measured PPG waveform of COVID period (1/19/2020 - 6/7/2021)

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

Measured: 120.3 mg/dL, 100%
First-order: 123.5 mg/dL, 97.3%
Second-order: 121.8 mg/dL, 98.7%
Third-order: 121.0 mg/dL, 99.4%

All three perturbed waveform predictions have the same shape similarity (i.e., same correlation coefficients of R=81%) in comparison against the measured COVID PPG. The slightly lower than 90% of R is due to the fact that the 3 predicted COVID waveforms are using the pre-COVID measured data as their baseline of calculation. Nevertheless, an 81% 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 using perturbation theory can be detected clearly via the summarized table shown below in the format of first-order, second-order, third-order:

Correlation: 81%, 81%, 81%
Accuracy: 97.3%, 98.7%, 99.4%

Figure 5 further demonstrates the comparison of 3 perturbed PPG waveforms versus both of measured PPG from High-Carbs and measured PPG from Low-Carbs of COVID period (1/19/2020 - 6/9/2021). It is quite obviously that all of these three perturbed COVID PPG curves are located within the boundary of high-carbs PPG curve and low carbs PPG curve despite of they were generated using pre-COVID PPG data as their baselines.

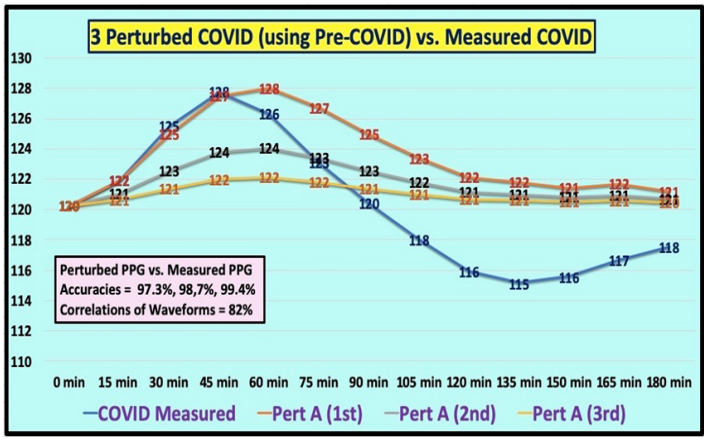

Figure 5: Comparison of three perturbed PPG waveforms versus both of measured PPG from High-Carbs and measured PPG from Low-Carbs of COVID period (1/19/2020 - 6/9/2021)

Conclusions

In summary, the obvious conclusion drawn from this research work is that the perturbation equation provides a predicted PPG with high accuracy and 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 97.3% prediction accuracy, the second-order perturbation provides 98.7% prediction accuracy, and the third-order perturbation delivers 99.4% prediction accuracy. All three perturbed PPG waveforms have equal level of waveform shape similarity with 81% versus the measured COVID PPG waveform. The lower than 90+% correlations are due to the selection of the pre-COVID PPG 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 [1-37].

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