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Research Article

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Application of Higher-Order Interpolation Perturbation Theory on Postprandial Plasma Glucose Waveform of a Single Lunch Based on GH-Method: Math-Physical Medicine (No. 426)

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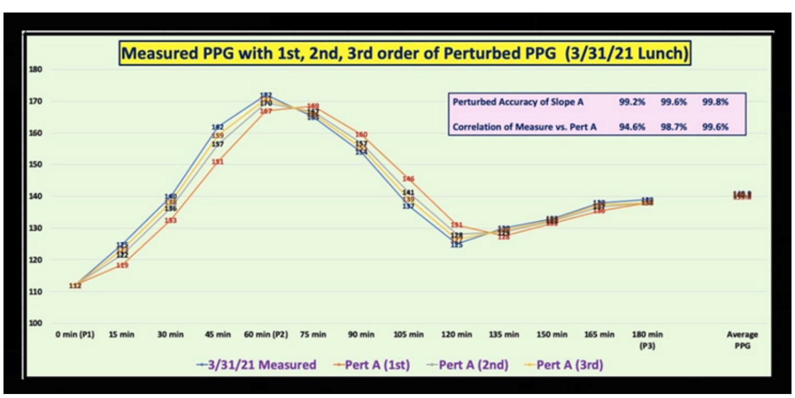
Abstract

In this particular research note, the author arbitrarily selects the postprandial plasma glucose (PPG) data and waveforms from his lunch on 3/31/21 as the reference base. He then applies the higher-order, including first-order, second-order, and third-order interpolation perturbation theory to generate three approximated PPG waveforms to compare them against the measured nonlinear PPG waveform.

The two major purposes of this study is to check the waveform shape similarity via correlation coefficients and the prediction accuracy via comparison of the averaged PPG values using the "higher order" interpolation perturbation theory.

One obvious conclusion can be drawn from this article is that the higher-order perturbation equation provides a better approximate solution. However, in reality, there are very few patients who understand the perturbation theory of quantum mechanics, let alone to be able to conduct the complex mathematical calculations in order to achieve their desired glucose projection.

In comparison, the linear elastic glucose theory (LEGT) does offer accurate enough information for diabetes patients and easier for them to learn how to control their daily glucose situations via a few conversion factors. Actually, it is intuitively acceptable to not-so-severe type 2 diabetes patients if they view the GH.p-Modulus as the conversion factor for the intake of carbs/sugar to increase the PPG amount; and the GH.w-Modulus as another conversion factor for the post-meal exercise to reduce the PPG amount, then they will be able to control their daily PPG level rather quickly and easily.



Introduction
In this particular research note, the author arbitrarily selects the postprandial plasma glucose (PPG) data and waveforms from his lunch on 3/31/21 as the reference base. He then applies the higher-order, including first-order, second-order, and third-order interpolation perturbation theory to generate three approximated PPG waveforms to compare them against the measured nonlinear PPG waveform.

The two major purposes of this study is to check the waveform shape similarity via correlation coefficients and the prediction accuracy via comparison of the averaged PPG values using the "higher order" interpolation perturbation theory.

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 or formulas 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 establish three "perturbed PPG" waveforms based on one function of the selected carbs/sugar intake amount as the perturbation factors, i.e. the "Equation of Slope". He uses the "measured nonlinear PPG" waveform as the "reference PPG" 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 types of ratios from carbs 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 form:

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

Where:
Y1 =
original glucose at time 1 on Y-scale
Y2 =
advanced glucose at time 2 on Y-scale

(Y2-Y1) = (Glucose at Time 2 - Glucose at Time 1)

The perturbation factor of ***slope*** is an arbitrarily selected real parameter that controls the size of the perturbation. The author has chosen a function of x amount i.e., the carbs/sugar intake amount, as the perturbation factor of slope which is further defined as follow:

Slope A= (Selected Carbs - Low-bound Carbs) / (High-bound Carbs - Low-bound Carbs)

Slope B= (Selected Carbs) / (High-bound Carbs)

*Based on the author's experience, users can select Slope A if they have two sets of glucose data and their associated carbs/sugar amount corresponding to a higher-bound carbs/sugar amount and a lower-bound carbs/sugar amount. Users can select Slope B if they have only one set of glucose data and use its associated carbs/sugar amount as the Reference base. Please be aware that **Slope B value is smaller than 1.0 by choosing the "selected perturbed" carbs as either the numerator or the denominator.***

*It should be noted that, for better and more accurate predicted glucose value, **the selected carbs amount should be within the range between the high-bound carbs and the low-bound carbs, where these two carbs values should be within 4 times in magnitude to each other.***

In this particular study, he choose Slope A as his equation of per action factor. He has already recorded two separated PPG waveforms with Carbs/sugar amount of 32 grams (high) and 22 grams (low). Now, he uses 27 grams (the mean of 32 and 22) as his selected carbs/sugar amount.

Results
Input Data of This Study
This particular lunch collected 13 glucose data at 15 minutes for each time interval, staring from the first bite of meal at 0-minute (11:30 for this case) through the PPG peak occurring around 60-minutes and then ending at 180-minutes after eating (14:30 for this case).

The author stopped his post-lunch walking steps of 6,000 when the PPG reached to 125 mg/dL at 120-minutes, but the excessive "left-over" energy bounced back to tilt the PPG curve upward until the PPG reached to 139 mg/dL at 180-minutes after his first bite of lunch. This phenomenon relates to "energy theory" of mechanical engineering.

The lunch consisted approximately 1.5 fist-sized portion of cooked white flour noodles (about 30 grams of carbs) with some boiled tomatoes and onions (about 2 grams of sugar). His post-lunch walking k-steps was 6.0 which indicated that he continuously walked for one hour from 60-minutes to 120-minutes with his normal walking speed of 100 steps per minute.

Graphic Figures of this Study

Figure 1 shows the photo of his cooked lunch meal with the quantity of white flour noodles. With a natural intelligence of visual check and nutrition data stored in his brain and his developed artificial intelligence tool, he can get the rough estimate Carbs/sugar amount equivalent to 1.5 fist-size portion of noodles which equals approximately 30 grams of carbohydrates. The combined small amount of boiled tomatoes and onions had approximately 2 grams of sugar.

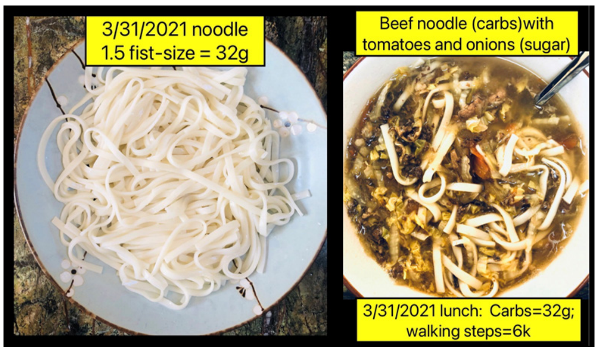


Figure 1: Noodle lunch photo of 3/31/2021

Figure 2 reflects the input data and calculated data of this lunch's measured nonlinear PPG waveform and the output results of combined measured PPG and three perturbed PPG waveforms using first-order, second-order, and third-order of interpolation perturbation equation using Slope A as the perturbation factor. *Since he chose the selected carbs of 27 grams which is located right in the middle of the low-bound carbs of 22 grams and high-bound carbs of 32 grams, his actual three calculated slopes are 0.5 for the first-order, 0.25 for the second-order, and 0.125 for the third-order.*

3/31/2021 Lunch PPG	3/31/21 Measured	Pert A (1st)	Pert A (2nd)	Pert A (3rd)
0 min (P1)	112	112	112	112
15 min	125	119	122	123
30 min	140	133	136	138
45 min	162	151	157	159
60 min (P2)	172	167	170	171
75 min	165	169	167	166
90 min	154	160	157	155
105 min	137	146	141	139
120 min	125	131	128	127
135 min	130	128	129	129
150 min	133	132	132	133
165 min	138	136	137	137
180 min (P3)	139	138	138	138
Average PPG	140.9	139.8	140.3	140.6
Carbs & Walking	High	Selected	Low	
Carbs grams	32	27	22	
Walking K-steps	6.00			
Perturbation Theory		1st order	2nd order	3rd order
Slope A=(Selected-Low)/(High-Low)		0.50	0.25	0.13
Slope B=Selected/High				
Perturbed Accuracy of Slope A		99.2%	99.6%	99.8%
Perturbed Accuracy of Slope B				
Correlation of Measure vs. Pert A		94.6%	98.7%	99.6%

Figure 2: Input data table and calculated perturbation results

Figure 3 demonstrates the conclusive Graphic results of this higher-order interpolation perturbation analysis. There are three major observations from analyzing this diagram. First, all of these 3 perturbed waveforms have similar shapes with the measure nonlinear PPG waveform with high correlations between 95% to ~100%. Second, the higher-order perturbed curve has better predicted glucoses, not only just the average PPG, but also every data point on the curve. That is why all of these 3 perturbed curves offer extremely high prediction accuracies between 99.2% to 99.8%. The third and most important point is that the third-order perturbed result is the best one.

The above-described 3 conclusions can be seen easily from the following summarized table in the format of first-order, second-order, and third-order:

Correlation: (94.6%, 98.7%, 99.6%)
Accuracy: (99.2%, 99.6%, 99.8%)

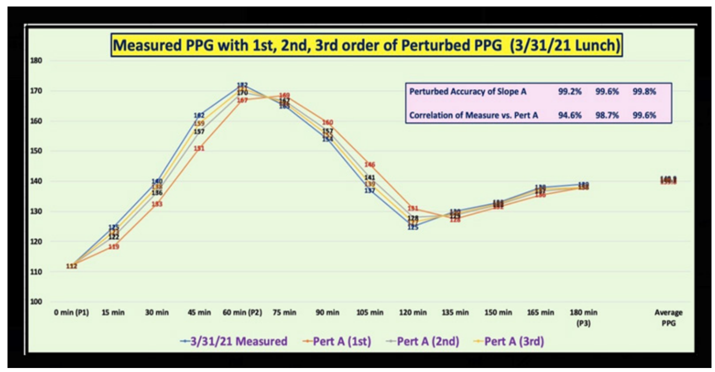


Figure 3: Measured PPG waveform vs. 1st, 2nd, and 3rd order of perturbed PPG waveforms

Figure 4 reveals three sets of comparison diagrams regarding correlation coefficients between measured PPG versus each perturbed PPG. At one glance of this figure, we can recognize both high correlation and high accuracy existing between the measured PPG and perturbed PPG.

The mathematical power of achieving approximation by perturbation theory can be seen again via the same data table shown above.

Correlation: (94.6%, 98.7%, 99.6%)
Accuracy: (99.2%, 99.6%, 99.8%)

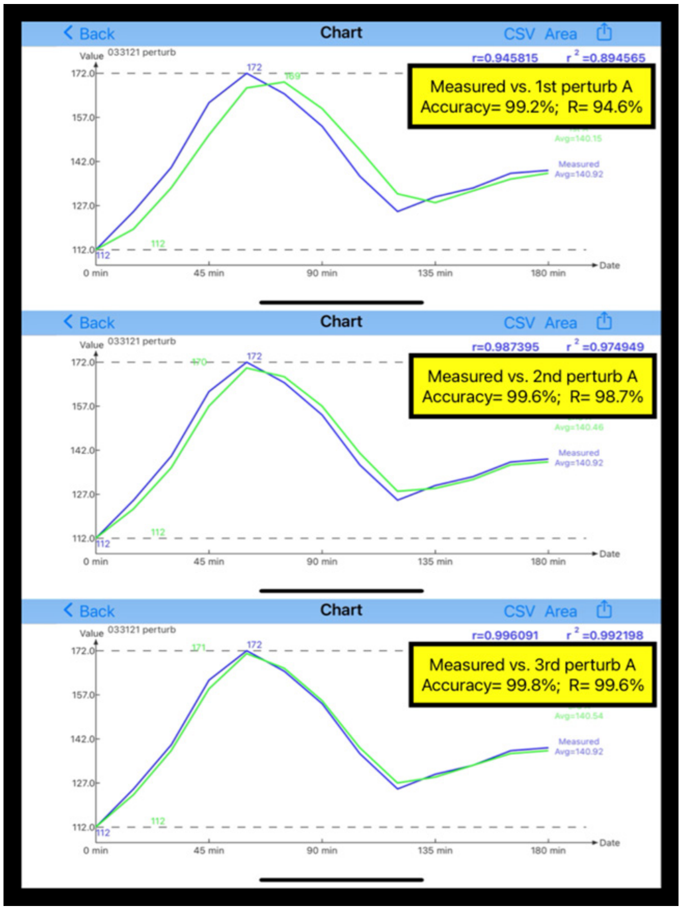


Figure 4: Correlations and Predicted Accuracies of 3 perturbed PPG waveforms vs. measured PPG waveform

Conclusions

One obvious conclusion can be drawn from this article is that the higher-order perturbation equation provides a better approximate solution. However, in reality, there are very few patients who understand the perturbation theory of quantum mechanics, let alone to be able to conduct the complex mathematical calculations in order to achieve their desired glucose projection.

In comparison, the linear elastic glucose theory (LEGT) does offer accurate enough information for diabetes patients and easier for them to learn how to control their daily glucose situations via a few conversion factors. Actually, it is intuitively acceptable to not-so-severe type 2 diabetes patients if they view the GH.p-Modulus as the conversion factor for the intake of carbs/sugar to increase the PPG amount; and the GH.w-Modulus as another conversion factor for the post-meal exercise to reduce the PPG amount, then they will be able to control their daily PPG level rather quickly and easily [1-35].

References

1. Hsu Gerald C (2021) Biomedical research using GH-Method: math-physical medicine, version 3 (No. 386).
2. Hsu Gerald C (2021) From biochemical medicine to math-physical medicine in controlling type 2 diabetes and its complications (No. 387).
3. Hsu Gerald C (2021) Methodology of medical research: Using big data analytics, optical physics, artificial intelligence, signal processing, wave theory, energy theory and transforming certain key biomarkers from time domain to frequency domain with spatial analysis to investigate organ impact by relative energy associated with various medical conditions (No. 397).
4. Hsu Gerald C (2021) Linear relationship between carbohydrates & sugar intake amount and incremental PPG amount via engineering strength of materials using GH-Method: math-physical medicine, Part 1 No. 346.
5. Hsu Gerald C (2021) Investigation on GH modulus of linear elastic glucose with two diabetes patients data using GH-Method: math-physical medicine, Part 2 No. 349.
6. Hsu Gerald C (2021) Investigation of GH modulus on the linear elastic glucose behavior based on three diabetes patients' data using the GH-Method: math-physical medicine, Part 3 No. 349.
7. Hsu Gerald C (2021) Coefficient of GH.f-modulus in the linear elastic fasting plasma glucose behavior study based on health data of three diabetes patients using the GH-Method: math-physical medicine, Part 4 No. 356. J App Mat Sci & Engg Res 4: 50-55.
8. Hsu Gerald C (2020) High accuracy of predicted postprandial plasma glucose using two coefficients of GH.f-modulus and GH.p-modulus from linear elastic glucose behavior theory based on GH-Method: math-physical medicine, Part 5 No. 357. J App Mat Sci & Engg Res 4: 71-76.
9. Hsu Gerald C (2021) Improvement on the prediction accuracy of postprandial plasma glucose using two biomedical coefficients of GH-modulus from linear elastic glucose theory based on GH-Method: math-physical medicine, Part 6 No. 358.
10. Hsu Gerald C (2021) High glucose predication accuracy of postprandial plasma glucose and fasting plasma glucose during the COVID-19 period using two glucose coefficients of GH-modulus from linear elastic glucose theory based on GH-Method: math-physical medicine, Part 7 No. 359.
11. Hsu Gerald C (2021) Investigation of two glucose coefficients of GH.f-modulus and GH.p-modulus based on data of 3 clinical cases during COVID-19 period using linear elastic glucose theory of GH-Method: math-physical medicine, Part 8 No. 360.
12. Hsu Gerald C (2020) Postprandial plasma glucose lower and upper boundary study using two glucose coefficients of GH-modulus from linear elastic glucose theory based on GH-Method: math-physical medicine, Part 9 No. 361. J App Mat Sci & Engg Res 4: 83-87.
13. Hsu Gerald C (2020) Six international clinical cases demonstrating prediction accuracies of postprandial plasma glucoses and suggested methods for improvements using linear elastic glucose theory of GH-Method: math-physical medicine, Part 10 No. 362. J App Mat Sci & Engg Res 4: 88-91.
14. Hsu Gerald C (2021) A special Neuro-communication influences on GH.p-modulus of linear elastic glucose theory based on data from 159 liquid egg and 126 solid egg meals using GH-Method: math-physical medicine, Part 11 No. 363. J App Mat Sci & Engg Res 5: 126- 131.

15. Hsu Gerald C (2020) GH.p-modulus study of linear elastic glucose theory based on data from 159 liquid egg meals, 126 solid egg meals, and 2,843 total meals using GH-Method: math-physical medicine, Part 12 No. 364. J App Mat Sci & Engg Res 4: 31-36.
16. Hsu Gerald C (2020) Detailed GH.p-modulus values at 15-minute time intervals for a synthesized sensor PPG waveform of 159 liquid egg meals, and 126 solid egg meals using linear elastic glucose theory of GH-Method: math-physical medicine, Part 13 No. 365. J App Mat Sci & Engg Res 4: 37-42.
17. Hsu Gerald C (2020) A lifestyle medicine model for family medical practices based on 9-years of clinical data including food, weight, glucose, carbs/sugar, and walking using linear elastic glucose theory and GH-Method: math-physical medicine (Part 14) No. 367. MOJ Gerontol Ger 5: 197-204.
18. Hsu Gerald C (2020) GH.p-modulus study during 3 periods using finger-piercing glucoses and linear elastic glucose theory (Part 15) of GH-Method: math-physical medicine No. 369. J App Mat Sci & Engg Res 4:31-36.
19. Hsu Gerald C (2020) GH.p-modulus study using both finger and sensor glucoses and linear elastic glucose theory (Part 16) of GH-Method: math-physical medicine (No. 370). J App Mat Sci & Engg Res 4: 62-64.
20. Hsu Gerald C (2020) A summarized investigation report of GH.p-modulus values using linear elastic glucose theory of GH-Method: math-physical medicine, Part 17 No. 371. J App Mat Sci & Engg Res 5: 113-118.
21. Hsu Gerald C (2021) An experimental study on self-repair and recovery of pancreatic beta cells via carbs/sugar intake increase and associated postprandial plasma glucose variation using linear elastic glucose theory (part 18) and GH-Method: math-physical medicine No. 396.
22. Hsu Gerald C (2021) Analyzing roles and contributions of fasting plasma glucose, carbs/sugar intake amount, and post-meal walking steps on the formation of postprandial plasma glucose using Linear Elastic Glucose Theory of GH-Method: math-physical medicine, LEGT Part 19 No. 401.
23. Hsu Gerald C (2021) Analyzing relations among weight, FPG, and PPG using statistical correlation analysis and Linear Elastic Glucose Theory of GH-Method: math-physical medicine, LEGT Part 20 No. 402.
24. Hsu, Gerald C (2021) Estimating cardiovascular disease risk and insulin resistance via transforming glucose wave fluctuations from time domain into associated energy in frequency domain and applying the linear elastic glucose theory of GH-Method: math-physical medicine, LEGT Part 21 No. 403.
25. Hsu Gerald C (2021) PPG magnitude and fluctuation study of three 346-days periods using time-domain and frequency domain analyses as well as linear elastic glucose theory (part 22) of GH-Method: math-physical medicine No. 411.
26. Hsu Gerald C (2021) Using 12-years glucoses including intermittent fasting glucose data, and high-carbs meals glucose data to study the suitability, lower-bound, and upper-bound of the linear elastic glucose theory based on GH-Method: math-physical medicine, Part 23 (No. 412).
27. Hsu Gerald C (2021) A case study of pre-virus period versus virus period applying wave theory, energy theory, Fourier transform, and linear elastic glucose theory (LEGT Part 24) to estimate risk probability of having a cardiovascular disease or stroke and achieving longevity based on GHethod: math-physical medicine (No. 413).
28. Hsu Gerald C (2021) A case study of three time periods applying wave theory, energy theory, Fourier transform, and linear elastic glucose theory (LEGT Part 25) to estimate risk probability of having a cardiovascular disease or stroke and achieving longevity based on GH-Method: math-physical medicine (No. 414).
29. Hsu Gerald C (2021) A summary report of 25 research articles utilizing linear elastic glucose theory based on GH-Method: math-physical medicine, LEGT Part 26 (No. 415).
30. Hsu Gerald C (2021) An artificial intelligence model applying linear elastic glucose theory to control diabetes and its complications to achieve longevity based on GH-Method: math-physical medicine, LEGT Part 27 (No. 416).
31. Hsu Gerald C (2017) Three GH-modulus for predicted glucose via LEGT linear PPG and HbA1C control based on 12-years lifestyle data and finger-pierced glucoses using GH-Method: math-physical medicine, LEGT Part 28 (No. 417).
32. Hsu Gerald C (2020) Applying first-order perturbation theory of quantum mechanics to predict and build a postprandial plasma glucose waveform (GH-Method: math-physical medicine) No. 152. Journal of Geriatric Research 4: 1-2.
33. Hsu Gerald C (2020) Applying the first-order interpolation perturbation method to establish predicted PPG waveforms based on carbs/sugar intake amounts using GH-Method: math-physical medicine (No.154). J App Mat Sci & Engg Res 4: 65-70.
34. Hsu Gerald C (2021) Application of perturbation theory, frequency domain energy theory, and linear elasticity theory to study and predict postprandial plasma glucose behaviors and their impact on internal organs of Type 2 diabetes patients based on GH-Method: math-physical medicine (No. 423).
35. Hsu Gerald C (2021) Application of perturbation theory and linear elasticity glucose theory (LEGT Part 31) on postprandial plasma glucose waveform of a single lunch based on GH-Method: math-physical medicine (No. 424).