ISSN: 2689-1204

Research Article

Journal of Applied Material Science & Engineering Research

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)

Gerald C Hsu

EclaireMD Foundation, USA

***Corresponding author**
Gerald C Hsu, EclaireMD Foundation, USA

Submitted: 16 July 2021; **Accepted**: 23 July 2021; **Published**: 05 Aug 2021

Citation: *Gerald C Hsu (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). J App Mat Sci & Engg Res, 5(2), 1-10.*

Abstract
The author combined three of his recent articles, No. 420, 421, and 422, where he utilized perturbation theory, frequency domain energy theory, and linear elasticity theory to study and predict postprandial plasma glucose (PPG) behaviors and their impact on internal organs of Type 2 diabetes patients. They are based on a collected PPG dataset from 2,128 low-carbs meals and 1,090 high-carbs meals within a time period from 5/5/2018 to 3/27/2021. For over the past decade, he has used his developed GH-Method: math-physical medicine methodology for most of his medical research work including this study.

The research tools he has chosen for this particular project include the following four major theories from mathematics, physics, engineering, and computer science:

1. Using the first-order perturbation theory in quantum mechanics to estimate and establish a different glucose waveform resulted from eating a different carbohydrates and sugar amount.
2. Using an existing PPG waveform in a time domain to transform it into a frequency domain via fast Fourier transform and signal processing techniques to study the relative energy level associated with PPG
3. Using theory of elasticity from strength of material, Young's modulus relating stress and strain, to GH.p-Modulus relating to carbs/sugar amount and incremental PPG amount, to construct a 'pseudo-linear" PPG and compare against the original nonlinear PPG waveform to obtain its accuracy of PPG predictability.
4. Using optical physics and artificial intelligence (AI) to develop an AI tool which links visible food colors, wavelength of different colors, internal molecular structures of food, ingredients of food (especially carbohydrates and sugar amount) based in 6 million collected food nutrition database. The fourth category of optical physics and AI is only mentioned and also utilized in his research work but will not be elaborated in the body of this article.

The author is a trained physicist, engineer, mathematician, and computer scientist academically and professionally. He does not have any advanced training in both biology and chemistry. Eleven years ago, he decided to save his life with the available resources in his toolbox when he was warned by three physicians regarding his poor health conditions and death threat from his diseases. Starting from 2010, he had no choice but to apply his learned knowledge to study and research on diseases, health, and death instead of using the traditional biochemical medicine approach like other medical research scientists.

During 2010-2013, he spent 4 years on studying internal medicine, endocrinology, diabetes, metabolism, and lifestyles. He focused on studying the "black box" of internal medicine and chronic diseases, especially diabetes, and their complications, such as heart attacks, strokes, kidney disease, etc.

Over the past 11 years, he has spent 30,000 hours on studying and researching medicine. During the research process, he had to take refresher courses by reviewing many subjects in mathematics, physics, and engineering in order to be able to conduct his own research work without the help from schools, professors, or medical doctors.

As of now, on March 30, 2021, his overall health condition has reached to its peak condition over the past 30 years. He is grateful for having the knowledge and experience he received and gained from both educational institutes and professional workplaces. He never thought that his background could apply and be used on medicine. The most rewarding aspect to him is that he saved his own life through his limited knowledge; therefore, this is the driving force pushing him to write this particular research note.

Introduction

The author combined three of his recent articles, No. 420, 421, and 422, where he utilized perturbation theory, frequency domain energy theory, and linear elasticity theory to study and predict postprandial plasma glucose (PPG) behaviors and their impact on internal organs of Type 2 diabetes patients. They are based on a collected PPG dataset from 2,128 low-carbs meals and 1,090 high-carbs meals within a time period from 5/5/2018 to 3/27/2021. For over the past decade, he has used his developed GH-Method: math-physical medicine methodology for most of his medical research work including this study.

The research tools he has chosen for this particular project include the following four major theories from mathematics, physics, engineering, and computer science:

1. Using the first-order perturbation theory in quantum mechanics to estimate and establish a different glucose waveform resulted from eating a different carbohydrates and sugar amount.
2. Using an existing PPG waveform in a time domain to transform it into a frequency domain via fast Fourier transform and signal processing techniques to study the relative energy level associated with PPG
3. Using theory of elasticity from strength of material, Young's modulus relating stress and strain, to GH.p-Modulus relating to carbs/sugar amount and incremental PPG amount, to construct a 'pseudo-linear" PPG and compare against the original nonlinear PPG waveform to obtain its accuracy of PPG predictability.
4. Using optical physics and artificial intelligence (AI) to develop an AI tool which links visible food colors, wavelength of different colors, internal molecular structures of food, ingredients of food (especially carbohydrates and sugar amount) based in 6 million collected food nutrition database. The fourth category of optical physics and AI is only mentioned and also utilized in his research work but will not be elaborated in the body of this article.

Methods

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.

The Author'S Case of Diabetes

The author was a severe type 2 diabetes patient since 1996. He weighed 220 lb. (100 kg) at that time. By 2010, he still weighed 198 lb. with an average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached to 1161 (high risk for CVD and stroke) and albumin-creatinine ratio (ACR) at 116 (high risk for chronic kidney disease). He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding the needs of kidney dialysis treatment and future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology with emphasis on diabetes and food nutrition. During 2015 and 2016, he developed four mathematical prediction models related to diabetes conditions: weight, PPG, fasting plasma glucose (FPG), and HbA1C (A1C). By applying his developed mathematical metabolism index (MI) model in 2014 and the four glucose prediction tools during 2015-2016, by the end of 2016, his weight was reduced from 220 lbs. (100 kg) to 176 lbs. (89 kg), waistline from 44 inches (112 cm) to 33 inches (84 cm), average finger-piercing glucose from 250 mg/dL to 120 mg/dL, and A1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medications starting since 12/8/2015.

In 2017, he had achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period of 2018 and 2019, he traveled to ~50 international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control caused by stress, dinning out frequently, post-meal exercise disruption, jet lag, along with the overall negative metabolic impact from the irregular life patterns; therefore, his glucose control was affected during the two-year period of 2018-2019.

He started his self-quarantined life on 1/19/2020. By the end of 2020, his weight was further reduced to 165 lbs. (BMI 24.4) and his A1C was at 6.2% without any medications intervention or insulin injection. In fact, with the special COVID-19 quarantine lifestyle in 2020, not only has he published ~400 medical papers in various journals, but he has also achieved his best health conditions for the past 26 years. These achievements are resulted from his non-traveling, low-stress, and regular daily life routines. Of course, his in-depth knowledge on chronic diseases, sufficient practical lifestyle management experiences, and his developed various high-tech tools have also contributed to his excellent health status since 1/19/2020.

On 5/5/2018, he applied a continuous glucose monitoring (CGM) sensor device on his upper arm and checks his glucose measurements every 15 minutes for a total of ~96 times each day. He has maintained the same measurement pattern to present day. Therefore, during the past 11 years, he could continuously investigate, study, and analyze his collected ~2 million data regarding his health status, medical conditions, and lifestyle details. He applies his knowledge, models, and tools from mathematics, physics, engineering, and computer science to conduct his medical research work. His entire medical research work is based on the aims of achieving both "high precision" with "quantitative proof" in the bio-medical findings, not just through linguistic expressions with qualitative words, vague statements, or complex medical terminologies.

Input Data for Time Domain

In this article, the author uses a self-monitoring glucose device (SMGD) to collect his glucose data (sensor glucoses) from 5/5/2018 to 3/27/2021 containing 1,057 days and 3,171 meals with 47 snacks.

In his collected glucose data, there are 96 data per day at 15 minutes as each time interval and 13 glucose data for each PPG time-period of 3 hours, from first-bite of meal at 0-minute through PPG peak usually at 60-minutes and cut-off time instant at 180 minutes after eating.

Among these 3,218 meals data, he selects 2,128 meals for the low-carbs category (0 gram to 15 grams with an average carbs amount at 7.2 grams per meal) and 1,090 meals for the high-carbs category (15.1 gram to 200 grams with an average carbs at 27.7 grams per meal).

First subject: Perturbation Theory

The author applies the first-order interpolation perturbation method to establish a predicted "perturbed PPG" waveforms based on different carbs/sugar intake amounts and "real-measured PPG" waveforms.

Normally, a given complex function can obtain certain approximated solutions through a class of simpler and approximated operations. A biomarker, such as PPG, has multiple influential factors, including carbs/sugar intake amount and post-meal exercise quantity, and other secondary factors. If we maintain the post-meal exercise amount at a constant level, then we only need to deal with a single variable of the carbs/sugar intake amount.

Most general complex problems can be expressed by the following polynomial function of nth degree:

Y= P(X)= A0 + A1*X**1 + A2*X**2 + ... + An*X**n

This nth degree polynomial function could be solved by approximating the Y-values based on the available data set with the help of some external but small "perturbation factor", such as a "slope", to adjust the neighboring datapoint on X-scale with a corresponding Y-value which is approximate to the original Y-value in the available data set. This mathematical approximation approach could be achieved through the interpolation tool with the perturbation method.

First, in many cases, this nth degree polynomial function could be further simplified via truncating off the higher order terms to achieve the following first-order polynomial function:

Y = f(X) = A0 + A1*X

Second, the above first-order polynomial function's approximate solution could be obtained through a specific "interpolation" or "extrapolation" method.

Interpolation is implemented within the range covered by data of both the PPG due to high-carbs amount (high glucose) and PPG due to low-carbs amount (low glucose). The interpolation method replaces Y (glucose level) with an easily calculated function, usually a polynomial and a simple straight line. In short, the interpolation method, also known as the intermediate value, is a scientific term that could be defined as arriving to unknown intermediate values (e.g., glucose level Y mg/dL) of a function by using known values (e.g., carbs amount X grams). For the complex problem of glucose variation study, this simplified equation can be expressed in the following format of the perturbation equation:

New glucose value of Y mg/dL corresponding to a new X carbs gram, where X carbs can be any amount within the range of a high-bound of carbs and a low-bound of carbs.
= function of carbs amount, i.e. f(X)
= Y1 + slope * (Y2 - Y1)
Y1 = original glucose on Y-scale
Y2 = advanced glucose on Y-scale

Where:

Slope A = (newly selected X carbs minus low-bound carbs) / (high bound carbs minus low-bound carbs)

We may use another formula such as Slope B:

Slope B = (low-bound carbs / high-bound carbs)

Where the high-bound carbs amount would be better if it is within the range of 4 times higher than the low-bound carbs amount.

The above descriptions of the perturbation theory can then be summarized into the following glucose perturbation equation:

Perturbation Equation

Perturbed Y
= Y1 + ***Slope*** ** (Y2 - Y1)*

Perturbed Glucose= *Glucose at T1 +* ***(Slope A or Slope B) **** *(Glucose at T2 - Glucose at T1)*

Where the slope is an arbitrarily selected real parameter that controls the size of the perturbation.

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

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

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 magnitude to each other.

The above-described steps of the calculation (the Perturbation Equation) have utilized an applied mathematics methodology of the "first-order interpolation perturbation method" which have been frequently used in quantum mechanics, fluid dynamics, and *solid mechanics.*

Second Subject: From Time Domain to Frequency Domain via Fourier Transform

Input Data for Time Domain

The author uses a SMGD to collect his glucose data (sensor glucoses) from 5/5/2018 to 3/27/2021. This time period contains 1,057 days and 3,171 meals with 47 snacks. He selects 2,128 meals for the low-carbs category, which has 0 gram to 15 grams with an average carbs at 7.2 grams per meal, and 1,090 meals for the high-carbs category, which has 15.1 gram to 200 grams with an average carbs at 27.7 grams per meal.

Frequency Domain of PPG Wave

After conducting his TD wave analysis, he then utilizes the Fast Fourier Transform (FFT) algorithm-based software program to convert his PPG waves from TD into FD in order to conduct his energy analysis.

PPG Fluctuation in TD and FD

He utilizes the maximum PPG minus the minimum PPG values as his PPG fluctuation data to conduct the TD wave analysis and then the FD energy analysis on the PPG fluctuation. This is similar to the concept of the ready-defined Glycemic Variability or GV in other medical publications.

Third Subject: Highlights of his Developed Linear Elastic Glucose Theory (LEGT)

The author self-studied internal medicine, including endocrinology and food nutrition over a 4-year period from 2010 to 2013. By the end of 2013, he has learned the primary connecting pathway moving from lifestyle to metabolism and immunity, which are two sides of the same coin, and then moving to both chronic diseases (caused by metabolic disorders) and infectious diseases (defended by our immune system), and finally to induce all kinds of diseases which lead to death.

Therefore, in 2014, he spent the entire year to develop a mathematical model of metabolism using topology concept of mathematics and finite element method of engineering which includes 10 categories and near 500 elements. All of its input data are more than 2 million thus far.

Due to the fact that PPG is the major factor of daily glucose composition and HbA1C measurement which affects diabetes conditions and its complications directly. Therefore, starting from 2015, he started to develop his prediction model for post-prandial plasma glucose (PPG). He has identified approximately 19 influential factors of PPG formation, where the health state of pancreatic beta cells insulin secretion (quantity) and insulin resistance (quality) are the most important and fundamental factor. Since it occupies more than 50% to 2/3 of total influences on PPG formation, therefore, he choose it as the "baseline PPG". Once removing this biomedical factor of insulin (50% to 67% of contribution), the other 18 remaining lifestyle details, ranging from 33% to 50%, contribute to the final PPG formation. Taking a macro-view of PPG formation, the pancreatic beta cells accounts for ~50% to 67% and diet of lifestyle provides ~50%, while diet of carbs/sugar and post-meal walking exercise would split the remaining 33% to 50% influences of the PPG formation. Although the combined diet and exercise are about 1/3 to 1/2 of PPG, but they are the only factors that diabetes patients can control on a daily basis. The current diabetes treatments by physicians to stabilize glucose levels are through medications and/or insulin injections. Unfortunately, this type of treatment attempts to alter the external symptom (i.e., output only) of the endocrinological diabetes disease but does not cure or even improve parts of the root cause. Only a long-term persistent effort of lifestyle management can truly "repair or improve" the damaged pancreatic beta cells but in a very slow process.

Starting from 2016, the author developed an intuition that the existence for a linear relationship between his measure PPG and carbs/sugar intake amount with a multiplying coefficient around 1.0 to 3.0 for a longer time-window or 1.8 to 2.5 for a specific shorter time-window. ***Since 2017, he has used 1.8-2.0 as his multiplier or GH.P-Modulus value on his carbs/sugar intake grams for estimating his incremental PPG amount.***

In order to solve the puzzle of the predicted PPG, the first task is to identify an accurate but easy way to estimate carbs/sugar intake amount. Utilizing optical physics (relationship among visible food color, external color's wavelength, internal molecular structure, and related nutritional ingredients), big data analytics (~6 million collected food nutritional data and 160 million digits of each meal photo), and AI (machine learning and auto-correction), he developed a computer software program to predict the carbs/sugar amount in his food or meals via a picture with a prediction accuracy of >99% (for over 3,000 meals or food pictures). He then applied this GH.p-Modulus of linear coefficient at 1.8 to 2.5 to multiply his estimated carbs/sugar amount from the AI tool in order to obtain the incremental PPG from food. This observed linear coefficient of 1.8 to 2.5 was his first identified GH-modulus, the GH.p-Modulus.

Diet is the most complicated part of this puzzle. Actually, from mathematics and physics viewpoints, the predicted PPG wave is a nonlinear mathematical problem with a dynamic physical phenomenon. In order to simplify this difficult task at hand, he has broken down this synthesized nonlinear system into 3 simpler linear systems or 3 straight-line segments. They are based on insulin, from the pancreatic beta cells to raise PPG from the ground level to the starting level of a PPG window, to further increase the PPG value via carbs/sugar intake, and then reduce the PPG value via post-meal waking steps or other exercises.

After 9-months of struggling during 2015-2016, in the middle of the night of 3/16/2016 in Las Vegas, he woke up from his sleep and discovered a strong correlation (>80% of R, the correlation coefficient) existing between his body weight and his collected FPG by having an "out-of-box" thinking. Both weight and FPG belong to the output category of the biomedical system, while lifestyle details belong to the input category. As a trained engineer, he was taught to always seek and identify those relationships existing between inputs and outputs, not just between output elements or between input elements. This discovery has proven that, in the biomedical system, its input elements and its output elements are actually inter-wined together.

From 2017 to 2020, he utilized 7 to 8 different research angles to investigate his pancreatic beta cells "self-repair" situation. Since there is no food or exercise associated with glucose during sleep hours to confuse the equation, by using the FPG data, a long-term record of FPG data or weight data can serve as a reliable "benchmark indicator" for the pancreatic health state. As a result, he identified his second GH-Modulus, the GH.f-Modulus, to transform either weight or FPG into baseline PPG.

Relatively speaking, exercise is a much easier subject to be dealt with. From his trial-and-error effort for finding the linear coefficient between the post-meal walking k-steps (1,000-steps) and reduction amount of PPG, he identified that PPG would be reduced by 5 to 6 mg/dL for every thousand steps after having meals (about 10 minutes of walking). Therefore, he has chosen -5 to -6 as his third GH-Modulus, the GH.w-Modulus. *For his own case, he choose -5.0 as his GH.w-Modulus value.*

By combining these three linear models together, he can then establish a "pseudo-linear" model (with 3 straight lines) to be served as his predicted LEGT PPG model as shown in Figure 1. This pseudo-linear model is superimposed with a synthesized nonlinear PPG wave model over 180 minutes time-span from his collected data over a period from 5/5/2018 to 3/27/2021.

Low-Carbs PPG (Slope A)	Low Real (2128)	Low Perturbed	High-Carbs PPG (Slope A)	High Real (1090)	High Perturbed
0 min	124	125	0 min	129	131
15 min	127	129	15 min	133	136
30 min	131	132	30 min	140	143
45 min	134	134	45 min	146	147
60 min	133	131	60 min	147	146
75 min	130	128	75 min	145	144
90 min	126	125	90 min	142	141
105 min	123	122	105 min	140	139
120 min	121	121	120 min	137	136
135 min	121	121	135 min	135	135
150 min	121	122	150 min	134	134
165 min	122	122	165 min	134	133
180 min	123	123	180 min	132	132
Average PPG	126	126	Average PPG	138	138
	Low bound Carbs	Selected Carbs		High bound Carbs	
Carbs grams	7.2	17.5	Carbs grams	27.7	

Low-Carbs PPG (Slope A)	Low Real (2128)	Low Perturbed	High-Carbs PPG (Slope A)	High Real (1090)	High Perturbed
0 min	124	125	0 min	129	131
15 min	127	129	15 min	133	136
30 min	131	132	30 min	140	143
45 min	134	134	45 min	146	147
60 min	133	131	60 min	147	146
75 min	130	128	75 min	145	144
90 min	126	125	90 min	142	141
105 min	123	122	105 min	140	139
120 min	121	121	120 min	137	136
135 min	121	121	135 min	135	135
150 min	121	122	150 min	134	134
165 min	122	122	165 min	134	133
180 min	123	123	180 min	132	132
Average PPG	126	126	Average PPG	138	138
	Low bound Carbs	Selected Carbs		High bound Carbs	
Carbs grams	7.2	17.5	Carbs grams	27.7	

Pertubation Equation Slope A = Glucose at T1 + ((Selected Carbs - Low bound carbs) / (High bound Carbs - Low bound Carbs)) * (Glucose at T2 - Glucose at T1)

Pertubation Equation Slope B = Glucose at T1 + (Low carbs / High Carbs) * (Glucose at T2 - Glucose at T1)

Make sue that the High-Carbs is at > 4 times level higher than the Low-Carbs value

Figure 1: Data table of Perturbation Theory Applications

If readers are interested in learning his step-by-step development and more detailed explanation of the predicted PPG equation using LEGT, they can read the author's published papers listed in References 4 through 29.

The LEGT equation is:

Predicted PPG= Baseline PPG + food induced incremental PPG + exercise induced incremental PPG

or,

Predicted PPG= (FPG * GH.f) + (Carbs/sugar * GH.p) + (post-meal walking k-steps * GH.w)

Based on his experiences on utilizing his GH-Modulus, the GH.f should fall into the range between 0.6 to 1.0. Frequently, for his own case, he choose 0.6 if using Weight or 0.97 to 1.0 if using FPG to start this linear equation calculation. He also chooses the GH.w as -5.0 for most of his exercise cases. Finally, *the GH.p-Modulus, the most important and difficult multiplier, defines the food induced incremental PPG. It is described again as follows:*

Food induced Incremental PPG= GH.p * carbs/sugar
or
GH.p = incremental PPG / carbs

In comparison with Young's modulus equation:

E = stress / strain

where higher E (stiff material) under the same stress would result into less strain.

If we consider carbs/sugar intake similar to stress and incremental PPG similar to strain, then ***the biomedical GH.p-modulus and engineering E of Young's Modulus would have a "reciprocal" relationship to each other.***

Therefore, a higher E of Young's modulus value is equivalent to a lower GH.p-Modulus value. If a higher E (stiff material) under the same stress level would result in a lower strain, which is similar to a lower GH.p-Modulus under the same carbs/sugar intake amount. This would result in a smaller amount of incremental PPG or the same GH.p-Modulus with the smaller carbs/sugar intake amount, resulting in a smaller amount of incremental PPG.

The above explanation provides an analogy of LEGT in biomedicine with the theory of elasticity in engineering.

Detailed Description of the Process using LEGT PPG Model

This section will illustrate the step-by-step development of his developed LEGT PPG model.

The first step discusses the baseline PPG which is the PPG level at the time instant of 0-minute i.e., the first bite of meal. As mentioned above, the early morning glucose level after waking up is a good benchmark indicator for the pancreatic health state. The FPG value has a different mechanism from the insulin generating capability, but it is directly proportional to the health state of the pancreatic beta cells insulin. Furthermore, FPG and weight have an extremely high correlation coefficient (>80%) between them (see Figure 2). Most diabetes patients know their daily weight, where some of them monitor their FPG on a regular basis. Therefore, depending on the data availability for either weight or FPG, patients may choose one of the following two equations to use:

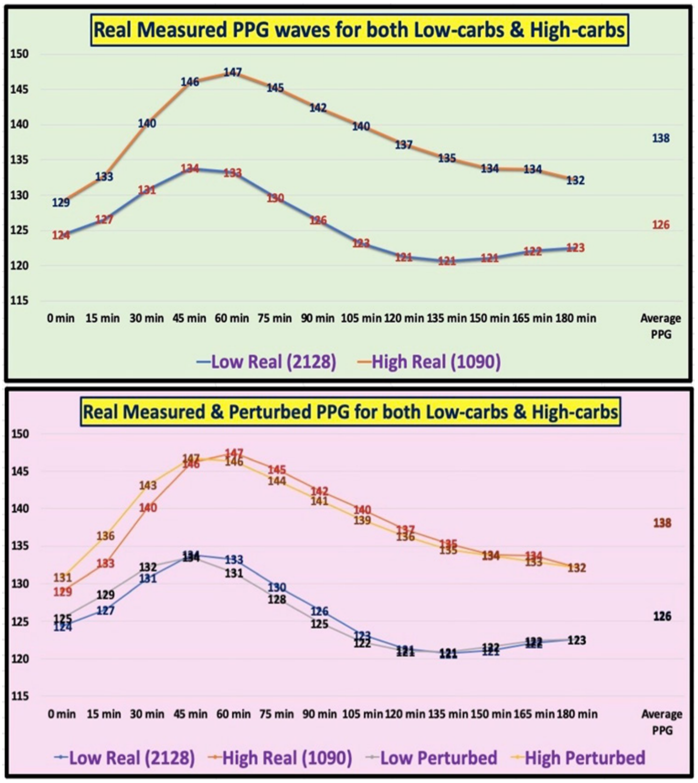


Figure 2: Graphic results of Perturbation Theory Applications

Baseline PPG = (0.6 - 0.7) * weight
Baseline PPG = (0.9 - 1.0) * FPG

The second step deliberates the rising PPG values from the starting time at 0-minute (defined as P1 value) to its peak at 45-minutes to 75-minutes. Let us assume the PPG value reaches to its peat at 60-minutes (defined as P2 value). During this time frame, the major fuel for this action of PPG rising is resulted from carbs/sugar intake with meal; therefore, the second segment of LEGT PPG equation is listed below:

Incremental PPG amount= P2 -P1= (carbs/sugar intake grams) * GH.p

Where GH.p-Modulus range is between 1.0 and 6.0., but the narrower range of 1.8-2.5 is more suitable for many patients under normal diet situations.

During this second step, patients can utilize the author's developed AI food nutrition program or rely on their own learned knowledge about carbs/sugar amount for each meal in completing the calculation for the second stage of diet.

The third step examines the PPG value reduction between time instant of 60-minutes to 180-minutes (defined as P3 value). It should add another time instant of 120-minutes (defined as Finger PPG value), where the PPG value corresponds to the advice of physicians to diabetes patients on measuring their PPG at two hours after the first bite of meals using the finger-piercing method. The PPG reduction amount can be calculated using the following equation:

PPG reduction amount= P2-P3= (post-meal walking k-steps) * GH.w

Where GH.w-Modulus range is between -5 and -6, but the selected GH.w value of -5 is more suitable for patients under normal walking conditions. Other types of exercise are also acceptable but its related GH.w value must be re-evaluated carefully via more experiments.

At this stage, a natural biomedical nonlinear PPG wave can then be replaced by three straight-lines and converts the nonlinear real PPG wave into a linear representation with a high accuracy of prediction. This is a simpler way to distinguish PPG situations.

For the LEGT PPG case, its average glucose levels are listed based on a set of geometry equations or using Equation A, which has the values of P1, P2, and P3.

Average sensor LEGT PPG= (2.5*P1+6.0*P2+4.5*P3)/13

and

Finger LEGT PPG= 0.87 * (sensor LEGT PPG at 120-minutes)= 0.87 * (P2+P3)/2

In this article, the author extended Equation A into Equation B, which uses weight or FPG, carbs/sugar intake amount, and post-meal walking k-steps, without involving P1, P2, and P3.

By starting with the following three initial definitions:

*P1 = GH.f * weight or FPG*
*P2 = P1 + GH.p * carbs*
*P3 = P2 + GH.w * k-steps*

We can then further derive them into the following Equation B:

Average LEGT sensor PPG= P1 + 0.8077 * (GH.p * Carbs) + 0.3462 * (GH.w * K-steps)

and

LEGT finger PPG (at 120-min)= 0.087 * (P1 + GH.P * Carbs) + 0.435 * (GH.w * K-steps) =

We can combine both Equation A and Equation B together as follows:

Average LEGT sensor PPG= (2.5 * P1 + 6.0 * P2 + 4.5 * P3)/13

= P1 + 0.8077 * (GH.p * Carbs) + 0.3462 * (GH.w * K-steps)

LEGT finger PPG (at 120-min)= 1/2 * (P2+P3)= 0.087 * (P1 + GH.P * Carbs) + 0.435 * (GH.w * K-steps)

The above descriptions, including the two important LEGT equations and three GH-Moduli, are the building blocks of the LEGT PPG program.

For most T2D patients, they just enter their weight or FPG values, average carb/sugar intake grams, and post-real walking k-steps, over a selected time period, into the program. Then, the AI assistant will perform all of the calculations.

Results

Figure 1 shows the input data of the measured PPG waveforms versus the perturbed PPG waveforms. It also lists those two slope equations (i.e., the "perturb factors"). Figure 2 depicts the graphic results of perturbation theory applications. It is obvious that these two perturbed curves are very close to the measured curves (i.e., high accuracy of this approximate solutions), for low-carbs case and high-carbs case, respectively.

Figure 3 reflects the input data of time domain and output data from frequency domain for both low-carbs case and high-carbs case. Figure 4 illustrates the graphic presentations of PPG amplitude comparison and PPG energy comparison. It is clear that high-carbs case provides more energy compared to the low-carbs case; and PPG fluctuations provide higher energy than PPG values. Therefore, diabetes patients should be cautious of their glucose fluctuation situation in addition to their average glucose value.

(5/5/18-3/27/21)	Low-Carbs	High-Carbs		
No. of Meals	2128	1090		
Finger PPG	108.7	120.0		
K-steps	4.323	4.490		
Carbs Range	0-15	15.1-200		
Carbs	7.2	27.7		
3/28/21 TD2FD	Low-Carbs	High-Carbs	Ratio (High/Low)	Comments
Total no. of meals	2128	1090	51%	
Weight	171	171	100%	
Sensor FPG	109	109	100%	Pancreas
Syn. PPG (Start @ 0-min)	124	129	104%	Neuro-science
Syn. PPG (Start - FPG)	15	20	130%	
Syn. PPG (Peak @ 60 min)	134	147	110%	Carbs
Syn. PPG (Peak - Start)	9	18	196%	
Syn. PPG (Mean)	129	138	107%	Carbs & Walking
K-line PPG (Max)	156	172	110%	
K-line PPG (Min)	105	110	105%	
K-line PPG Fluctuation (Max-Min)	51	62	122%	
Synthesized PPG (Max-Min)	44	46	105%	
Carbs/Sugar intake grams	7.2	27.7	385%	3.85 times higher
Post-Breakfast Walking K-Steps	4.3	4.5	104%	same walking
Finger PPG	109	120	110%	@120-min
10/19/20-3/1/21 (Breakfast) Freq.-D	Low-Carbs	High-Carbs	Ratio (High/Low)	Comments
FD (PPG Energy Y)	360	621	172%	FD-Y: 70% higher
FD (PPG Max-Min Energy Y)	413	705	171%	
FD (PPG value Area)	358,220	446,829	125%	FD Area: 25% higher
FD (PPG Max-Min Area)	411,975	509,431	124%	

Figure 3: Data table of Frequency Domain Energy Analysis

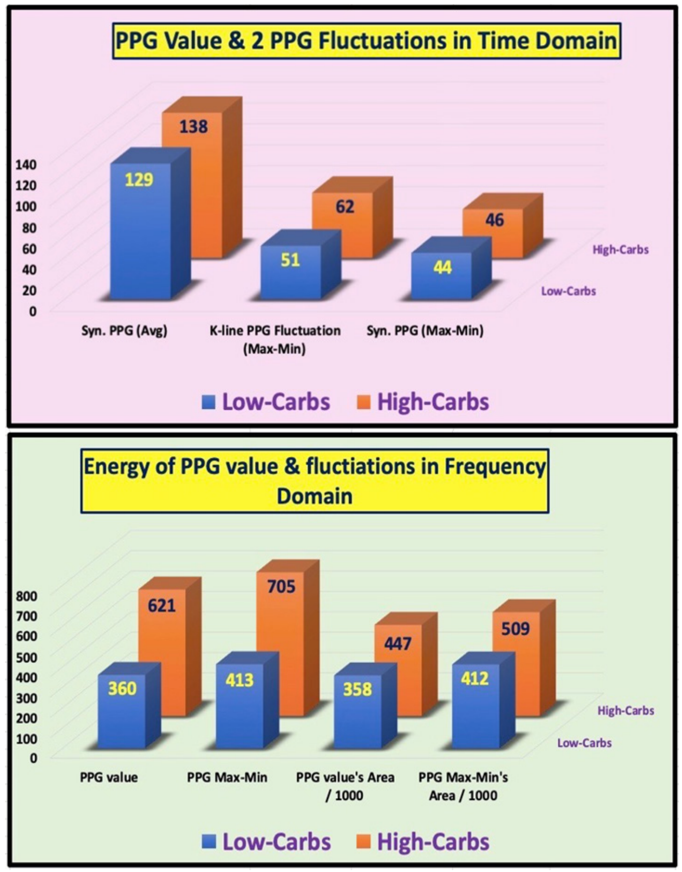


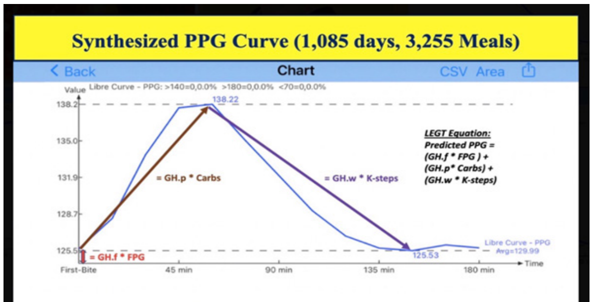
Figure 4: Graphic results of Frequency Domain Energy Analysis

Figure 5 reveals the 3 linear LEGT segments of a synthesized PPG waveform and the roles of each of three GH-Moduli in the linear elastic glucose theory. It also provides input data and shows the LEGT related calculation process step-by-step. Figure 6 provides the graphic results using LEGT model to compare against the collected real nonlinear PPG waveform. In comparing the average PPG values, the LEGT model could provide an accuracy rate greater than 99%.

(5/5/18-3/27/21)	Low-Carbs	High-Carbs
No. of Meals	2128	1090
Weight	171	171
Finger PPG	108.7	120.0
K-steps	4.323	4.490
Carbs Range	0-15	15.1-200
Carbs	7.2	27.7

Average sensor LEGT PPG
*Equation A = (2.5*P1+6.0*P2+4.5*P3)/13*
*Equation B = P1 + 0.8077 * (GH.p * Carbs) + 0.3462 * (GH.w * K-steps)*

Figure 5: Three linear segments of a synthesized PPG wave and data table of LEGT & 3 GH-Moduli



(3/28/2021) LEGT Analysis	5/5/18-3/27/21	5/5/18-3/27/21
Sensor Glucose (mg/dL)	Low-Carbs	High-Carbs
Weight	171	171
Sensor FPG	109	109
GH.f	1.14	1.18
PPG Baseline = (GH.f*FPG)	124	129
No. of Meals	2128	1090
Finger PPG	117	113
Carbs/Sugar	7.2	27.7
GH.p	1.60	0.80
GH.p*Carbs	12	22
P1 = Syn. PPG @ start (BaselinePPG)	124	129
Syn. PPG (Start @ 0-min)	124	129
Syn. PPG (Peak @ 60 min)	134	147
P2 = Syn PPG @ Peak = start + GH.p*Car	136	151
Walking K-steps	4.3	4.5
GH.w	-5.00	-5.00
GH.w * K-steps	-22	-22
P3 = PPG due to GH-p & Walking	114	129
Syn. PPG @ 180-min	123	132
Sensor Glucose (mg/dL)	Low-Carbs	High-Carbs
Equation A = Syn. PPG (Avg)	*126*	*139*
Equation B = Syn. PPG (Avg)	*128*	*139*
Measured PPG	*126*	*138*

Figure 6: PPG Graphic results of LEGT linear model vs. measured nonlinear waveform

For more detailed interpretation and explanation regarding biomedical applications using these three engineering and physics theories, readers can review No. 420, 421, and 422, along with the referenced articles in this paper to get a better understanding on this subject.

Conclusions

The author is a trained physicist, engineer, mathematician, and computer scientist academically and professionally. He does not have any advanced training in both biology and chemistry. Eleven years ago, he decided to save his life with the available resources in his toolbox when he was warned by three physicians regarding his poor health conditions and death threat from his diseases. Starting from 2010, he had no choice but to apply his learned knowledge to study and research on diseases, health, and death instead of using the traditional biochemical medicine approach like other medical research scientists.

During 2010-2013, he spent 4 years on studying internal medicine, endocrinology, diabetes, metabolism, and lifestyles. He focused on studying the "black box" of internal medicine and chronic diseases, especially diabetes, and their complications, such as heart attacks, strokes, kidney disease, etc.

Over the past 11 years, he has spent 30,000 hours on studying and researching medicine. During the research process, he had to take refresher courses by reviewing many subjects in mathematics, physics, and engineering in order to be able to conduct his own research work without the help from schools, professors, or medical doctors.

As of now, on March 30, 2021, his overall health condition has reached to its peak condition over the past 30 years. He is grateful for having the knowledge and experience he received and gained from both educational institutes and professional workplaces. He never thought that his background could apply and be used on medicine. The most rewarding aspect to him is that he saved his own life through his limited knowledge; therefore, this is the driving force pushing him to write this particular research note [1-33].

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 lin-

ear 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: 62-64.