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Research Article

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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)

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Abstract

This article is Part 6 of the author's linear elastic glucose behavior study, which focuses on the prediction accuracy of postprandial plasma glucose (PPG) over the pre-virus period, from 9/1/2015 to 12/31/2019, and the COVID-19 virus period, from 1/1/2020 to 11/6/2020. This research is the continuation of his previous five studies on linear elastic glucose behaviors. As a comparison, this study also utilized his developed artificial intelligence (AI) software to predict his PPG values.

The main objective is to offer numerical proof for the high prediction accuracy of PPG based on linear elastic glucose theory with two biomedical coefficients of GH-modulus and the adjustment of the baseline PPG (i.e., pancreatic beta cells' health conditions) during the COVID-19 virus period.

Based on the author's engineering background, he defines the GH.p-modulus to represent the linear elastic PPG behaviors followed by his defined GH.f-modulus to represent his linear elastic FPG behaviors.

He then discovered that these two unique biomedical coefficients are dependent upon health conditions of a patient, i.e. his/her severity level of obesity and diabetes. Furthermore, he also observed that these two biomedical coefficients behave like a "pseudo-constant" during a period of 3 to 4 months. The average lifespan of red blood cells are approximately 115 to 120 days. Red blood cells carry both oxygen and glucose to circulate the entire body to transport the needed nutrition and energy to maintain the body's operations, especially for the internal organs.

As the next step, he applied the linear elastic glucose equation on certain selected meals and observed extremely high accuracies of predicted PPG values. He then followed his research by choosing annualized PPG data over a period of 5+ years to do his calculations. He also observed their impressively high prediction accuracies.

In this article, he compares his predicted PPG values against the finger measured PPG values over the pre-virus period (9/1/2015 - 12/31/2019) and virus period (1/1/2020 - 11/6/2020) to see the subtle differences of the prediction accuracy due to different lifestyles using both AI approach and NI approach.

The virus period has achieved 99.98% accuracy with NI and 98.44% accuracy with AI, while the pre-virus period has achieved 99.65% accuracy with NI and 99.30% accuracy with AI. The reason for the virus period in achieving a slightly higher prediction accuracy using NI than the pre-virus period is that the virus period has implemented an adjustment of a lower baseline PPG. ***In summary, when a patient implements a stringent lifestyle management program, his/her weight would be reduced, and then lead into a lower glucose level, both FPG and PPG.***

The linear elastic predicted PPG equation cited in this article is simple enough for patients to apply on their weight and diabetes control. The only required input data are body weight, carbs/sugar intake amount, and post-meal walking steps, without the problematic collection in obtaining glucose data.

Introduction

This article is Part 6 of the author's linear elastic glucose behavior study, which focuses on the prediction accuracy of postprandial plasma glucose (PPG) over the pre-virus period, from 9/1/2015 to 12/31/2019, and the COVID-19 virus period, from 1/1/2020 to

11/6/2020. This research is the continuation of his previous five studies on linear elastic glucose behaviors. As a comparison, this study also utilized his developed artificial intelligence (AI) software to predict his PPG values.

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Methods

Background
To learn more about the author's GH-Method: math-physical medicine (MPM) methodology, readers can refer to his article to understand his developed MPM analysis method in Reference 1.

Highlights of his Related Research
In 2015 and 2016, the author decomposed the PPG waveforms (data curves) into 19 influential components and identified carbs/sugar intake amount and post-meal walking exercise contributing to approximately 40% of PPG formation, respectively. Therefore, he could safely discount the importance of the remaining ~20% contribution by the 16 other influential components.

In March of 2017, he also detected that body weight contributes to over 85% to fasting plasma glucose (FPG) formation. Furthermore, in 2019, he identified that FPG could serve as a good indicator of the pancreatic beta cells' health status; therefore, he can apply the FPG value (more precisely, 97% of FPG value) to serve as the baseline PPG value to calculate the PPG incremental amount in order to obtain the predicted PPG.

In 2018, based on his collected ~2,500 meals and associated sensor PPG waveforms, he further applied the perturbation theory from quantum mechanics, using the first bite of his meal as the initial condition to extend and build an entire PPG waveform covering a period of 180 minutes, with a 95% of PPG prediction accuracy.

In 2019, all of his developed PPG prediction models achieved high percentages of prediction accuracy, but he also realized that his prediction models are too difficult for use by the general public. The above-mentioned sophisticated methods would be difficult for healthcare professionals and diabetes patients to understand, let alone use them in their daily life for diabetes control. As a result, he supplemented his complex models with a simple linear equation of predicted PPG (see References 2, 3, 4, and 12).

Here is his simple linear formula

Predicted PPG= FPG * M1 + (carbs-sugar * M2) - (post-meal walking k-steps * M3)

Where M1, M2, M3 are 3 multipliers.

After lengthy research, trial and error, and data tuning, he finally identified the best multipliers for FPG and exercise as 0.97 for M1 and 5.0 for M3. In comparison with PPG, the FPG is a more stabilized biomarker since it is directly related to body weight, not food or exercise. We know that weight reduction is a hard task. However, weight is a calmer and more stabilized biomarker in comparison to glucose which changes from minute to minute with a bigger magnitude of fluctuation. The influence of exercise (specifically, post-meal walking steps) on PPG (41% contribution and >80% negative correlation with PPG) is almost equal to the influence from the carbs/sugar intake amount on PPG (39% contribution and >80% positive correlation with PPG). In terms of intensity and duration, exercise is a simple and straightforward subject to study. Especially, normal-speed walking is a safe and effective form of exercise for the large portion of diabetes patients, particularly senior citizens.

The parameters, FPG and walking, have a lower chance of variation for the author. However, for some diabetes patients, he recommends them to keep the multiplier M3 as a variable if their exercise patterns are different and changing (i.e., dynamic).

The relationship between food nutrition and glucose is a complex and difficult subject to fully understand and effectively manage due to many types of available food, in terms of both quality and quantity of meals, with different carbs/sugar contents. For example, in the author's developed database of food material and nutritional ingredients, it contains over six million data. As a result, the author decided to implement two multipliers, M1 for FPG and M3 for exercise, as the two "constants", and keep M2 as the only "variable" in his PPG prediction equation.

Therefore, an easier linear equation for predicted PPG is developed and listed below:

*Predicted PPG= (0.97*FPG) +(Carbs&sugar * M2) - (post-meal walking k-steps * 5)*

He further created two new terms for his developed two linear elastic glucose coefficients:

Term 1
GH.p-modulus = M2

Term 2
*The incremental PPG from diet= Predicted PPG - baseline PPG (i.e. 0.97 * FPG) + (walking * 5)*

Coefficient 1 for PPG
GH.p-modulus= (Incremental PPG)/(Carbs&sugar)

Coefficient 2 for FPG
GH.f-modulus = (FPG) / (Weight)

After combining the above 2 terms and 2 coefficients, he obtained the following linear equation of predicted PPG:

Predicted PPG = (0.97 * GH.f-modulus * Weight) +(GH.p-modulus * Carbs&sugar) - (post-meal walking k-steps * 5)

By using this equation, a patient only needs the data of body weight, carbs & sugar intake amount, and post-meal walking steps to calculate the predicted PPG without obtaining any measured glucose data.

AI versus NI

In 2016, he utilized optical physics, big data analytics, and artificial intelligence (AI) techniques to develop a customized computer software to predict PPG based on the patient's food pictures or meal photos. This sophisticated AI approach and iPhone APP software product have reached to a 98.8% prediction accuracy based on ~6,000 meal photos.

Each photo of food or meal on the iPhone contains ~20 million pixels and each pixel requires 8 unique combination of alpha-numerical digits to represent the uniqueness of a pixel. Therefore, there are ~160 million pixels contained in a picture with many different types and shades of multiple colors. Different color's wavelength is closely related to different molecular structures of the food ingredients. Therefore, through this optical physics approach combined with AI technique, his developed software can quickly figure out the estimated carbohydrates and sugar amount of that particular food or meal. Using this estimated carbs/sugar amount and above predicted PPG equation, a predicted PPG value can be calculated and then compared against the finger-piercing measured PPG value to obtain AI % of prediction accuracy.

The author has spent past 10 years to study endocrinology, metabolism, and food nutrition. Therefore, he has also accumulated vast amount of knowledge of internal medicine and food nutrition in his brain. There are many complicated and deep relationships which cannot be easily programmed into his software program entirely. Besides, the retina can recognize and capture more sophisticated images and is more capable than any advanced camera. After consuming each meal, the author always input two sets of carbs/sugar intake amount data into his software, NI and AI. Here NI stands for natural intelligence which means to use his eyes and brain to make his decision regarding carbs/sugar intake amount. His developed software can quickly provide the results via both AI approach and NI approach.

Stress, Strain, & Young's Modulus

Prior to his medical research work, he was an engineer in the various fields of structural engineering (aerospace, naval defense, and earthquake engineering), mechanical engineering (nuclear power plant equipments, and computer-aided-design), and electronics engineering (computers, semiconductors, graphic software, and software robot).

The two biomedical coefficients of GH-modulus mentioned above were inspired by his prior knowledge in the theory of elasticity in strengths of engineering materials which has the following engineering equation developed in 1807 by a British scientist, Thomas Young:

Stress = Young's Modulus * Strain

(Note: Young's modulus and the two biomedical coefficients, both GH.f-modulus and GH.p-modulus, are reciprocal to each other.)

The following excerpts come from internet public domain, including Google and Wikipedia:

Strain - ε

Strain is the "deformation of a solid due to stress" - change in dimension divided by the original value of the dimension - and can be expressed as

$\varepsilon = dL / L$

where

ε *= strain (m/m, in/in)*

dL = elongation or compression (offset) of object (m, in)

L = length of object (m, in)

Stress - σ

Stress is force per unit area and can be expressed as

$\sigma = F / A$

where

σ *= stress (N/m2, lb/in2, psi)*

F = applied force (N, lb)

A = stress area of object (m2, in2)

Stress includes tensile stress, compressible stress, shearing stress, etc.

E, Young's Modulus

It can be expressed as:

$$E = \text{stress} / \text{strain} = \sigma / \varepsilon = (F / A) / (dL / L)$$

where

E = Young's Modulus of Elasticity (Pa, N/m2, lb/in2, psi) was named after the 18th-century English physicist Thomas Young.

Elasticity

Elasticity is a property of an object or material indicating how it will restore it to its original shape after distortion. A spring is an example of an elastic object - when stretched, it exerts a restoring force which tends to bring it back to its original length (Figure 1).

Plasticity

When the force is going beyond the elastic limit of material, it is into a plastic zone which means even when force is removed, the material will not return back to its original state (Figure 1).

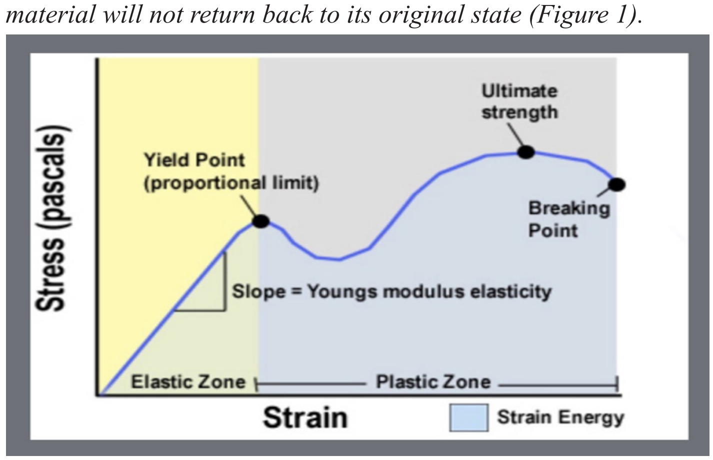

Figure 1: Stress-Strain-Young's modulus, Elastic Zone vs. Plastic Zone

Based on various experimental results, the following table lists some Young's modulus associated with different materials:

Nylon: 2.7 GPa
Concrete: 17-30 GPa
Glass fibers: 72 GPa
Copper: 117 GPa
Steel: 190-215 GPa
Diamond: 1220 GPa

Young's modules in the above table are ranked from soft material (low E) to stiff material (higher E)."

Professor James Andrews taught the author linear elasticity at the University of Iowa and Professor Norman Jones taught him nonlinear dynamic plasticity at Massachusetts Institute of Technology. These two great academic mentors provided him the necessary foundation knowledge to understand these two important subjects in engineering.

Data Collection

The author is a 73-year-old male with a 25-year history of T2D. He began collecting his carbs/sugar intake amount and post-meal walking steps on 6/1/2015. In order to achieve the data integrity and stability in his 90-days moving average calculation, he omitted the first three-months data. Therefore, from 9/1/2015 to 11/6/2020 (1,906 days), he has collected 7 data per day, i.e. weight, one FPG, three PPG, carb/sugar intake amount, and post-meal walking steps. He utilized these 13,342 data of 1,906 days to conduct this study.

The period of 9/1/2015 to 12/31/2019 is already his "better-controlled" diabetes period, where his average daily glucoses is maintained at 116 mg/dL (<120 mg/dL, the normal range). He named this period as his "linear elastic zone" of diabetes health. It should also be noted that in 2010, his average glucose was 280 mg/dL and HbA1C was 10%, while taking three diabetes medications. The strong chemical interventions from various diabetes medications would seriously alter glucose physical behaviors. He called the period prior to 2015 as his "nonlinear plastic zone" of diabetes health.

It should be pointed out that, this year of 2020 is his "best-performed" health period due to a stabilized routine and without any traveling lifestyle during the COVID-19 quarantined period. During this special period, his 90-days average daily glucose dropped to 101 mg/dL and his weight went below 170 lbs. (BMI <25). He reduced his weight from above 200 lbs. down to approximately 175 lbs. in 2015 and maintained that level for 5 years. This means that his pancreatic beta cells' health condition reached to the best state" in his 25 years of diabetes history.

Results

Listed below are his summarized key data of his body weight (lbs.) and baseline PPG (mg/dL) during the non-virus period (9/1/2015 - 12/31/2019) and virus period (1/1/2020 - 11/6/2020). Please note that the baseline PPG is moving in a downward trend from ~100 mg/dL in the pre-virus period toward ~90 mg/dL in the virus period.

Y2017: 178 lbs., 102 mg/dL
Pre-virus: 173 lbs., 99 mg/dL
Virus: 171 lbs., 98 mg/dL
11/2020: 167 lbs., 96 mg/dL

The above data have used the following formula and coefficient:

*baseline PPG= (GH.f-modulus * 0.97 * FPG)*

GH.f-modulus= 0.59

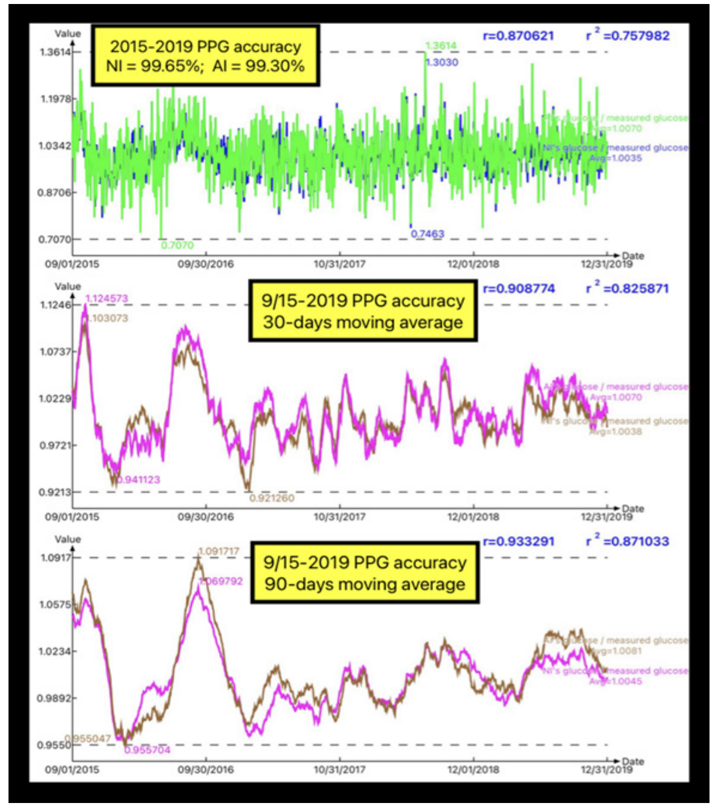

Figure 2: NI 99.65% and AI 99.30% of Pre-virus period (9/1/2015 - 12/31/2019)

Figure 2 shows the comparison between NI % (99.65%) and AI % (99.30%) using the "AI predicted" PPG vs. finger-measured PPG during the pre-virus period. The NI prediction is 0.35% higher than the AI prediction which means that the human brain is slightly better than the computer brain (CPU plus data storage).

Figure 3 depicts the comparison between NI % (99.98%) and AI % (98.44%) using the "AI predicted" PPG vs. finger-measured PPG during the virus period. The NI prediction is 1.54% higher than AI prediction which means that the human brain is better than computer brain (CPU plus data storage) again.

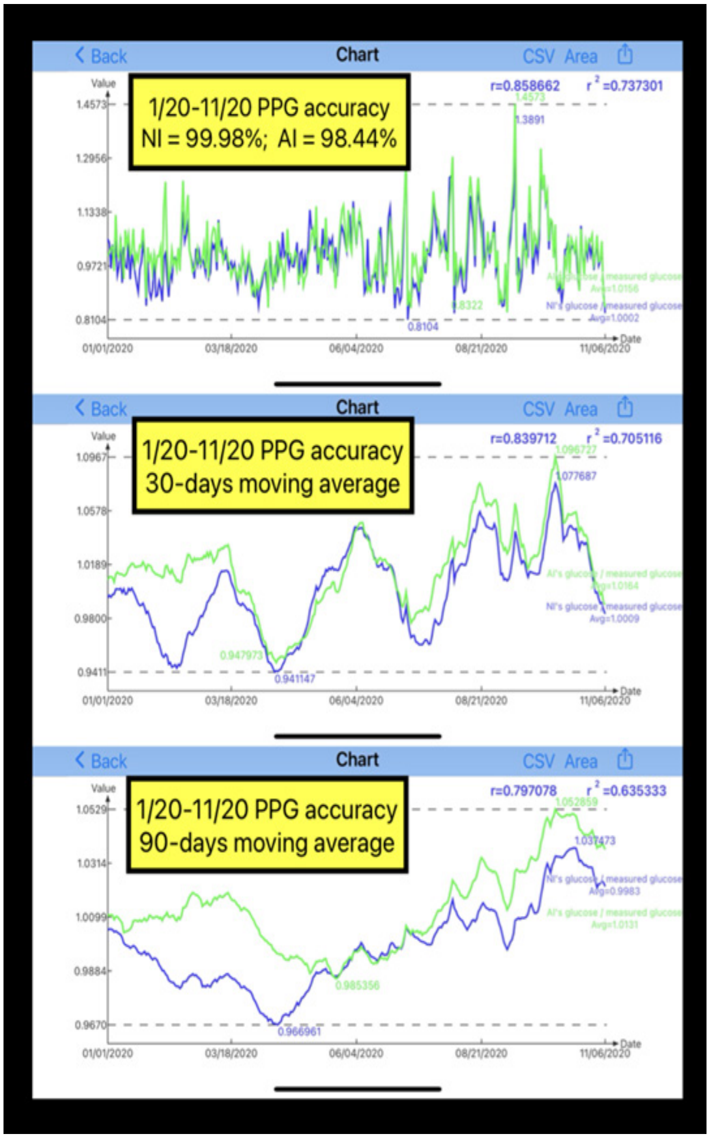

Figure 3: NI 99.98% and AI 98.44% of Virus period (1/1/2020 - 11/6/2020)

Both NI and AI have produced extremely high accuracies of the predicted PPG. However, the human brain still beats the computer with AI by 0.35% to 0.54%. The subtle differences of the phenomena observed by the human eyes and the vast learned knowledge stored and processed by the human brain are always superior to any computer. Theoretically, when and if AI can store all of the people's correct knowledge and high intelligence along with collecting everything from the human brain, then the AI system can then defeat the human's natural intelligence. Of course, this is just the author's personal opinion.

Another observation is that the author's health condition has reached to the best state for the past 25 years of history with obesity and diabetes. In his previous research, he has already identified that his pancreatic beta cells are repairing themselves at a slow rate of 2.7% per year over the last 6 to 8 years (Reference 14). This improvement on his insulin function reflects his downward trend of his baseline PPG value. The above-mentioned phenomenon and necessary system adjustment have already been inserted into his AI software algorithm recently for the time period after 1/1/2010.

Conclusions

Based on the author's engineering background, he defines the GH.p-modulus to represent the linear elastic PPG behaviors followed by his defined GH. f-modulus to represent his linear elastic FPG behaviors.

He then discovered that these two unique biomedical coefficients are dependent upon health conditions of a patient, i.e. his/her severity level of obesity and diabetes. Furthermore, he also observed that these two biomedical coefficients behave like a "pseudo-constant" during a period of 3 to 4 months. The average lifespan of red blood cells are approximately 115 to 120 days. Red blood cells carry both oxygen and glucose to circulate the entire body to transport the needed nutrition and energy to maintain the body's operations, especially for the internal organs.

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Acknowledgement

Foremost, I would like to express my deep appreciation to my former professors: professor James Andrews at the University of Iowa, who helped develop my foundation in basic engineering and computer science, and professor Norman Jones at the Massachusetts Institute of Technology, who taught me how to solve tough

scientific problem through the right attitude and methodology.

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