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A Postprandial Plasma Glucose Magnitude and Fluctuation Study for Three Periods Using Time-Domain, Frequency Domain Analyses, and linear Elastic Glucose Theory of GH-Method: Math-Physical Medicine, Part 22 (No. 409)

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Abstract

The author uses his self-monitoring glucose device (SMGD) to collect glucose data (sensor glucoses) from 5/5/2018 to 3/7/2021 of 1,023 breakfasts. He selects three equal period of 346 days each to conduct the glucose behavior study. In this article, Period A of Y18-Y19 and Period B of Y19-Y20 is known as the ***traveling periods****, and Period C of the COVID-19 quarantine timeframe is known as the* ***virus period.***

This investigation contains two parts. The first part is the study of sensor-collected *postprandial plasma glucose* (PPG) magnitude and their associated relative energies. The second part is the study of the *PPG wave fluctuations or glycemic variability (GV)* i.e., the maximum PPG value minus the minimum PPG value, for the PPG fluctuations and their corresponding relative energies.

At first, the author utilizes wave theory to study the mean values of PPG waves, which are the Y-amplitude of a glucose curve in a time domain (TD). He then applies signal processing technique and Fast Fourier Transform (FFT) operation to convert these PPG wave data of TD into a frequency domain (FD). In his previous research, he has proven that the Y-axis magnitude (Y-amplitude) of FD is related to the relative energy of the wave in TD.

In addition, from basic physics, he has learned that any TD's waves contain an energy level, which is directly proportional to the square of the amplitude of the wave in TD.

Therefore, by using the PPG magnitude in TD collected from these three equal-length time periods, he further verifies that the approach using "amplitude square" has achieved a similar pattern which is directly proportional to the calculated energy levels using the approaches of both "frequency domain's Y-amplitude" or "frequency domain area".

In this way, he can then quickly estimate the relative energy levels associated with different glucose levels to understand the different degree of organ impact resulting from the relative energies. The relative energies are generated by their associated glucoses directly and also carried by red blood cells circulating through the blood vessels to various organs in the body. Glucose is a double-edged sword where it supplies the nutrition and energy to meet the organ's needs and demands. However, the "excessive" amount of energy (diabetes) would damage the organs at the same time, which causes many types of complications to different organs.

The human organs and glucoses have their own different behaviors and biochemical interpretations, but at the same time, they also display and present certain interesting physical phenomena with specific numerical characteristics that follow basic physics theories and principles. These observed physical phenomena or puzzles can definitely be interpreted or resolved using mathematical equations or certain tools.

There are four key conclusions drawn from this investigation:

1. From a macro-viewpoint, the overall data pattern study shows that all of TD and FD numbers are remarkably close to each other for Periods A and B. However, Period C has demonstrated a better and healthier period in terms of PPG magnitudes, PPG fluctuations and their relative energies. This means that ***the virus period's quiet and non-traveling lifestyle has offered a better control of diabetes and its complications than the traveling periods.***
2. From a micro-viewpoint, the glucose and relative energy dif-

ferences between the higher-valued traveling periods and lower-valued virus period, using the virus period as the baseline of 100%, are very obvious. ***The excessive amount of differences for the PPG value is 12%, PPG value energy is 6-7%, PPG fluctuation is 27%, and PPG fluctuation energy is 17-31% between traveling periods and virus period.***

3. From the observation of higher PPG fluctuation magnitudes and their associated energies, we can also conclude that ***even the PPG fluctuation carries less energy than the PPG magnitude, but with a more violent PPG fluctuation of 17-31% added energy could cause additional damage to the internal organs than the mean or average glucose value, such as the HbA1C.***
4. From the linear elastic glucose theory analysis results, the two traveling periods have comparable values to each other in weight, FPG, post-meal walking steps, and PPG. All of them are higher than the virus period. However, despite a carbs/sugar intake amount of 12.8 grams in Period B which is lower than Period A of 15.9 grams and Period C of 14.0 grams. The Period B's GH.p Modulus value of 3.61 is slightly higher than the 2.95 from Period A and 3.15 from Period C. This indicates that ***his diabetes control and health state of both glucose and insulin in Period B (the heaviest traveling period) is worse than both Period A and Period C.***

Introduction

The author uses his self-monitoring glucose device (SMGD) to collect glucose data (sensor glucoses) from 5/5/2018 to 3/7/2021 of 1,023 breakfasts. He selects three equal period of 346 days each to conduct the glucose behavior study. In this article, Period A of Y18-Y19 and Period B of Y19-Y20 is known as the ***traveling periods,*** and Period C of the COVID-19 quarantine timeframe is known as the ***virus period.***

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Therefore, by using the PPG magnitude in TD collected from these three equal-length time periods, he further verifies that the approach using "amplitude square" has achieved a similar pattern which is directly proportional to the calculated energy levels using the approaches of both "frequency domain's Y-amplitude" or "frequency domain area".

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Methods and Results

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 and albumin-creatinine ratio (ACR) at 116. He also suffered from five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his needs of kidney dialysis treatment and his future high risk of dying from his severe diabetic complications.

In 2010, he decided to self-study endocrinology, diabetes and food nutrition. During 2015 and 2016, he developed four prediction models related to diabetes conditions, i.e., weight, postprandial plasma glucose (PPG), fasting plasma glucose (FPG), and HbA1C (A1C). As a result, from using his developed mathematical metabolism index (MI) model and those four prediction tools, by 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), averaged finger glucose from 250 mg/dL to 120 mg/dL, and HbA1C from 10% to ~6.5%. One of his major accomplishments is that he no longer takes any diabetes medications since 12/8/2015.

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

By 2020, his weight was further reduced to 165 lbs. (BMI 24.4) and his HbA1C was at 6.2% without any medications intervention or insulin injection. Actually, during 2020 with the special COVID-19 quarantined lifestyle, not only has he published approximately 400 medical papers in journals, but he has also achieved his best health conditions for the past 26 years. These good results are due to his non-traveling, low-stress, and regular daily life routines. Of course, his strong knowledge of chronic diseases, practical lifestyle management experiences, and his developed various high-tech tools contribute 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 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 medical research work is based on the aims of achieving both "high precision" with "quantitative proof" in his medical findings.

TD & FD Analyses, PPG Magnitude & Fluctuation

During the period from 5/5/2018 to 3/7/2021, he segregated his collected glucose data into three separated but with equal-days periods as follows:

Period A: (346 days)
Period B: (346 days)
Period C: (346 days)

After conducting a TD analysis, he then utilizes the FFT algorithm-based software program to convert his PPG waves from a TD into a frequency-domain to conduct his FD analysis.

He utilizes the maximum PPG minus the minimum PPG, as the fluctuation value for his PPG wave fluctuations data, to conduct both TD analysis and FD analysis of PPG fluctuation. His defined PPG fluctuation is similar to the concept developed by other medical research scientists regarding the "Glycemic Variability or GV".

Graphic Results

Figures 1 shows his data table which contains input data, his TD analysis results and FD analysis results for both PPG magnitude and PPG fluctuation. The summary of these results can be found in the first and second parts of the Conclusions section.

Time Period	5/5/18 - 4/15/19	4/16/19 - 3/26/20	3/27/20 - 3/7/21
Breakfast (10/15/2020-3/5/2021)	Period A (18-19)	Period B (19-20)	Period C (20-21)
No. of Days	346	346	346
No. of Meals	1095	1043	1019
Finger PPG	117	113	107
Carbs/Sugar grams	15.9	12.8	14.0
Post-meal Walking Steps	4329	4316	4469
Sensor FPG	113	113	102
Sensor PPG	134.45	134.71	120.25
Sensor (PPG-FPG)	22	21	19
FD PPG Y-Amp	216.37	225.42	204.63
FD PPG Area	74678	77470	70098
TD PPG value: (Current/Period C)	112%	112%	100%
FD PPG Y-Amp: (Current/Period C)	106%	110%	100%
FD PPG Area: (Current/Period C)	107%	111%	100%
TD PPG Max-Min	48	48	37
FD PPG Fluc. Y-Amp	266	237	203
FD PPG Fluc. Area	91700	81528	69887
TD PPG value: (Current/Period C)	112%	112%	100%
TD PPG Fluc.: (Current/Period C)	127%	127%	100%
FD PPG Fluc. Y-Amp: (Current/Period C)	131%	117%	100%
FD PPG Fluc. Area: (Current/Period C)	131%	117%	100%

Figure 1: Data table of TD & FD

In summary, Period C (virus period) has lower values for the magnitudes of FPG, PPG, PPG-FPG, and all of TD & FD analysis results than Periods A and B (traveling periods). Their carbs/sugar intake amount and post-meal waking steps are comparable to each other, except for Period B which has the lowest amount of carbs (12.8 grams). The implication of this lower carbs intake amount can be found in the linear elastic glucose theory analysis (Figure 7).

Figure 2 depicts the days selected for the beginning and ending dates for each period.

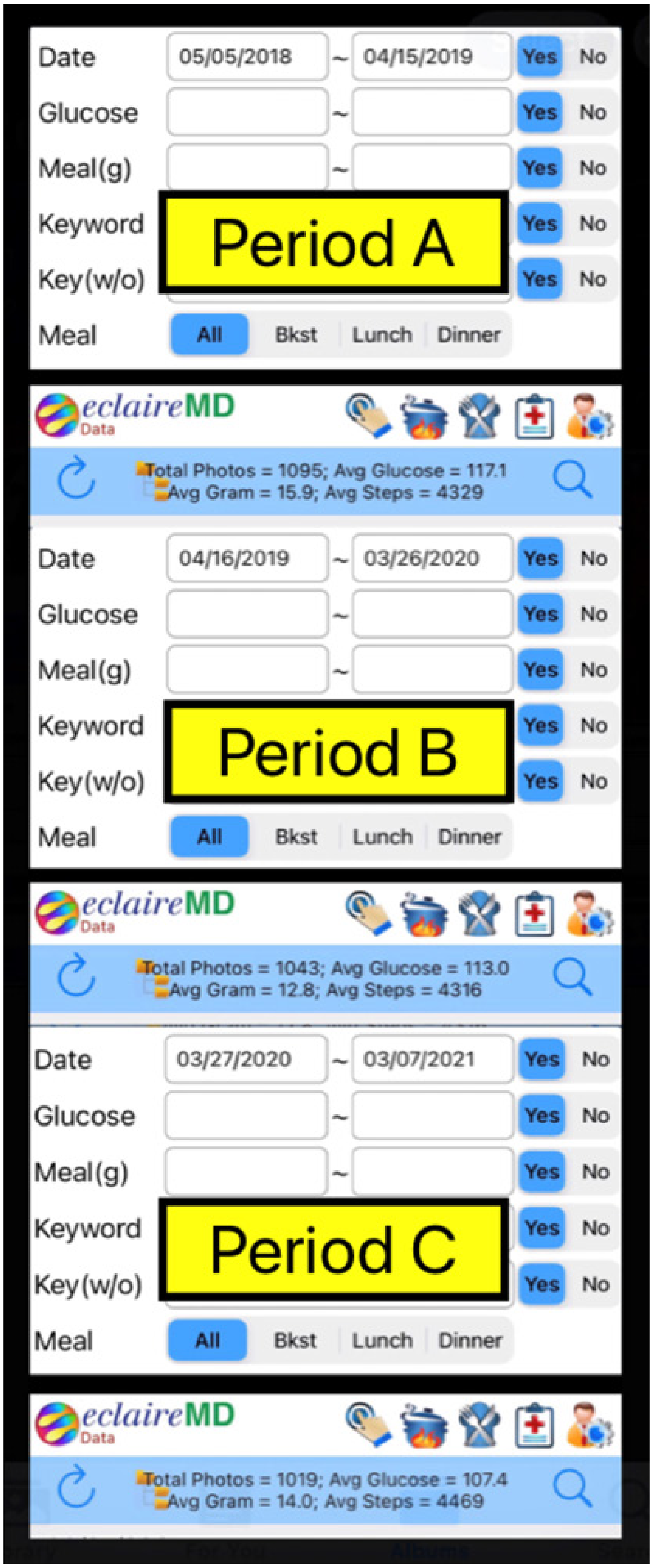

Figure 2: Time frames and input data of 3 Periods

Figure 3 reveals the comparison results from both synthesized PPG and Candlestick PPG K-line model for the three periods.

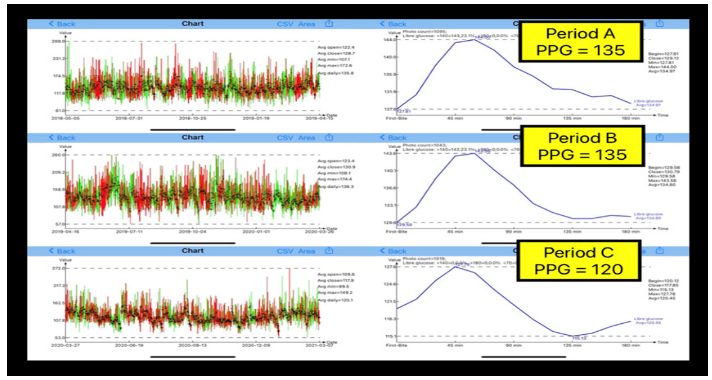

Figure 3: Synthesized and K-line PPG of 3 periods

It should be noted that *the extremities (i.e., the maximum and minimum values) in the K-line model would be smoothed off by the "averaging process" of producing a synthesized PPG curve* of 364 days (more than 1000 meals worth of data) for each period. Therefore, in theory, he could use the K-line model to determine his "real" extremity data of PPG. However, due to the lack of a corresponding wave output format from the K-line model, he cannot perform the necessary FFT operation directly. Therefore, he still uses his daily Max-Min wave from TD to conduct his FD analysis which would definitely affect the data accuracy to some degree for the less magnitude of PPG fluctuations.

Figure 4 illustrates the real daily data of weight, FPG, and PPG for the three periods.

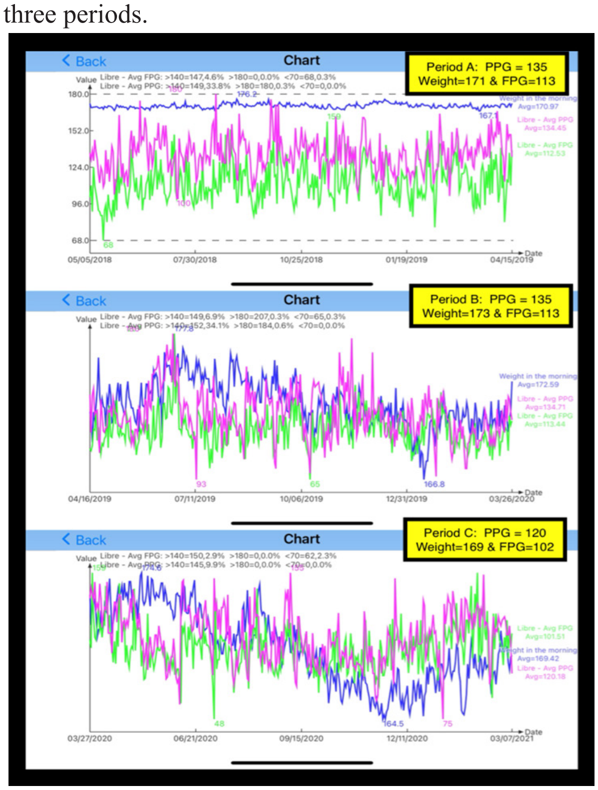

Figure 4: TD Daily curves of weight, FPG, PPG of 3 periods

Figure 5 reflects the 30-days moving average curve of weight, and 90-days moving average curve of both FPG and PPG for the three periods. From Figure 5, we can observe the similar moving patterns between FPG and PPG for the three periods, despite having different influential factors of the glucose formation. This correlation study also offers some additional information regarding FPG and PPG using their physical phenomena observation and numerical analysis.

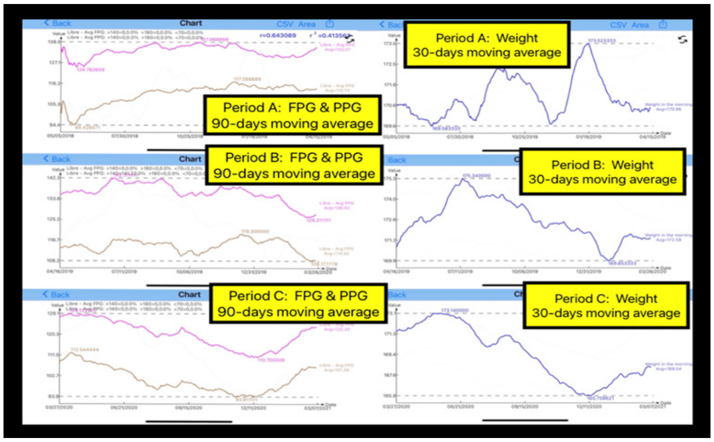

Figure 5: TD moving average curves of weight (30 days), FPG, & PPG (90 days) of 3 periods

Figure 6 combines 12 TD and FD wave diagrams together using the PPG value and PPG fluctuation for three periods. In the FD diagrams, we can see the Y-amplitude in FD and the total frequency area of FD for both PPG magnitude and PPG fluctuation which represent the relative energy of PPG.

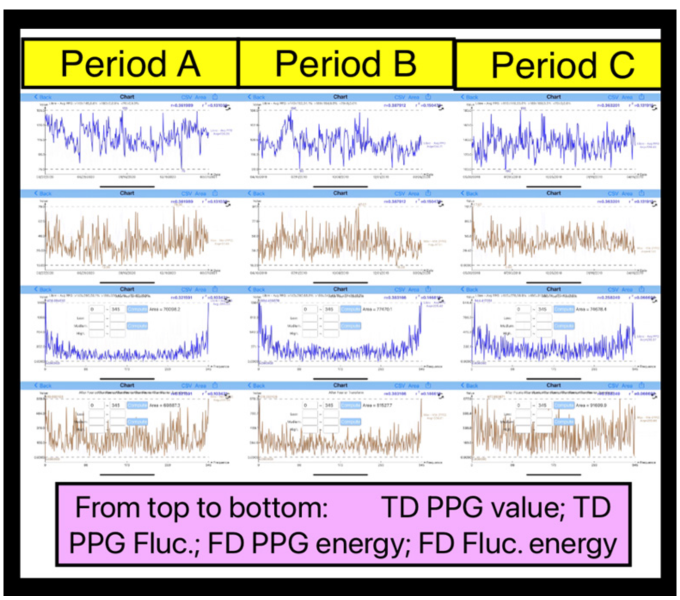

Figure 6: TD (wave theory) and FD (energy theory) of PPG values and PPG fluctuations (max-min)

Figure 7 signifies the numerical analysis of calculating the respective GH.p Modulus for each period using the author's developed linear elastic glucose theory (see multiple papers listed in reference section). Despite similar values of weight, FPG, exercise, and measured PPG in the two traveling periods, his slightly less amount of 12.8 grams of carbs/sugar in Period B (in comparison with the 15.9 grams in Period A) demands a slightly higher GH.p of 3.61 in Period B than 2.95 in Period A in order to converge his predicted PPG with his measured sensor PPG.

Breakfast (10/15/2020-3/5/2021)	Period A (18-19)	Period B (19-20)	Period C (20-21)
Weight	171	173	169
Sensor FPG	113	113	102
GH.f	0.97	0.97	0.97
PPG Baseline = (GH.f*FPG)	109	110	98
Carbs/Sugar (grams)	15.9	12.8	14.0
GH.p	2.95	3.61	3.15
GH.p*Carbs	47	46	44
Walking K-steps	4.3	4.3	4.5
GH.w	-5.0	-5.0	-5.0
K-steps*(-5)	-22	-22	-22
Predicted PPG (mg/dL)	134.45	134.71	120.25
Measured PPG (mg/dL)	134.45	134.71	120.25

Figure 7: Linear elastic glucose theory application of PPG analysis (Period B is relatively worst period from comparison of sensor FPG, sensor PPG, and GH.p Modulus)

Conclusions

The human organs and glucoses have their own different behaviors and biochemical interpretations, but at the same time, they also display and present certain interesting physical phenomena with specific numerical characteristics that follow basic physics theories and principles. These observed physical phenomena or puzzles can definitely be interpreted or resolved using mathematical equations or certain tools.

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are higher than the virus period. However, despite a carbs/sugar intake amount of 12.8 grams in Period B which is lower than Period A of 15.9 grams and Period C of 14.0 grams. The Period B's GH.p Modulus value of 3.61 is slightly higher than the 2.95 from Period A and 3.15 from Period C. This indicates that ***his diabetes control and health state of both glucose and insulin in Period B (the heaviest traveling period) is worse than both Period A and Period C [1-34].***

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