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Research Article

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A Study of the Postprandial Plasma Glucose Waves and Fluctuations of 63 Fasting and 43 Non-Fasting Meals at Breakfast Using Time and Frequency Domains Plus Wave Along with Energy Theories of GH-Method: Math-Physical Medicine (No. 405)

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Abstract

This particular study investigates a few postprandial plasma glucose (PPG) characteristics, including glucose waves and wave fluctuations or glycemic variability (GV) of 106 breakfasts from 11/5/2020 to 2/22/2021, which include 63 fasting and 43 non-fasting meals.

At first, the author utilizes wave theory to study PPG waves in time domain. He then applies signal processing techniques and Fast Fourier Transform program to convert these PPG waves into frequency domain. He can then estimate the relative energy levels associated with different glucoses of both fasting and non-fasting situations to understand the degree of organ impact related to these energies generated from or carried by glucoses in the blood system.

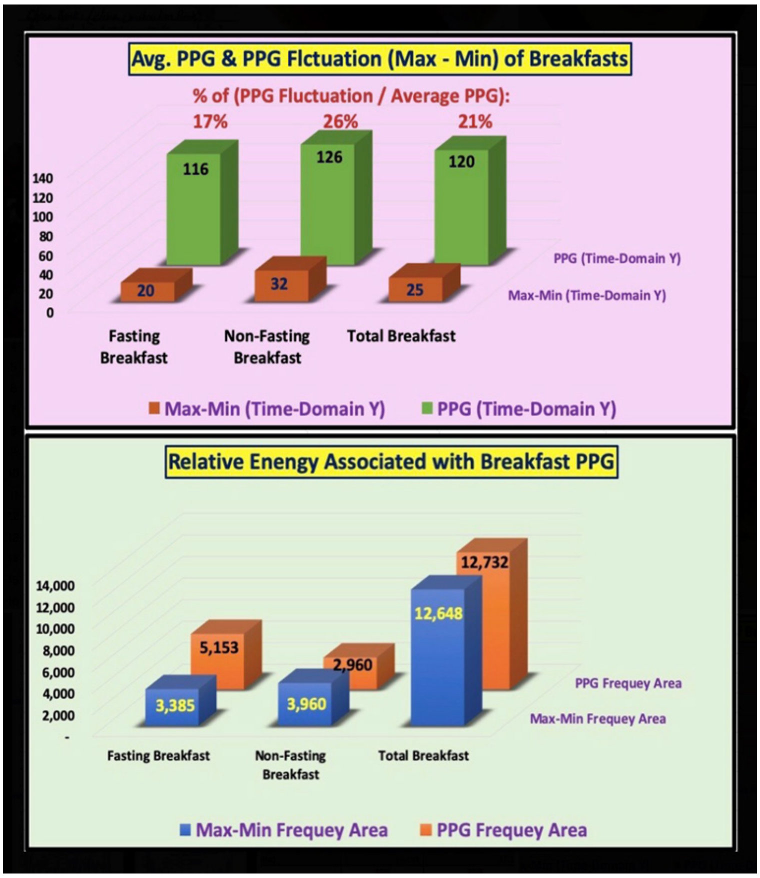
In summary, from the time domain analysis, the non-fasting's average PPG value is 15 mg/dL, which is 14% higher than the fasting's average PPG; and the non-fasting's peak PPG value is 21 mg/dL, which is 19% higher than the fasting's peak PPG value. Even the PPG wave fluctuations (Max.-Min.) of the non-fasting is 12 mg/dL, which is 60% higher than the fasting. It is interesting to observe that the fasting glucose wave still has fluctuations even though it is much "calmer".

On the other hand, from the frequency domain analysis, there are two observations described below:

1. *Relative energy associated with PPG wave reveals that non-fasting is 43% lower than fasting. This observation is counter to the author's intuitive feeling; however, this phenomenon is due to the higher amplitude (Y-value) result of the frequency domain after the Fourier Transform operation from the time domain. In other words, this characteristic of glucose energy corresponding to different frequencies in frequency domain is different from the characteristic of glucose corresponding to various times in time domain.*
2. *The relative energy associated with PPG wave fluctuations reflects that non-fasting is 17% higher than fasting which is due to the difference of 12 mg/dL, which is 60% of PPG fluctuation (Max - Min) in time domain. Besides, the Fourier Transform operation did not change the PPG fluctuation's characteristics in its frequency domain.*

Introduction

This particular study investigates a few postprandial plasma glucose (PPG) characteristics, including glucose waves and wave fluctuations or glycemic variability of 106 breakfasts from 11/5/2020 to 2/22/2021, which include 63 fasting and 43 non-fasting meals.



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In order to provide a clearer explanation of the different research methods and their connection with various research results, the author decided to combine the sections of Methods and Results into one segment to deliver better illustrations at each stage of the process.

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 the medical findings, not just through linguistic expressions of qualitative words, vague statements, or complex terminologies.

Input Data for Time Domain

During the period from 11/5/2020 to 2/22/2021, there are 106 days which include 63 days of fasting, where the author drinks tea only, and 43 days of non-fasting meals. For the follow-on analysis, he defines N as the components or segments in both time and frequency domains with N=42 for non-fasting, N=63 for fasting, and N=105 for total period.

The following table lists his key input data in the format of carbs/sugar intake grams, post-breakfast walking k-steps, finger-piercing measured PPG in g/dL, sensor collected PPG in mg/dL, percentage of difference between sensor PPG and finger PPG:

Fasting:
(0.0, 4.2, 106, 110, 4%)
Non-Fasting:
(7.5, 4.4, 115, 125, 9%)
Total:
(3.0, 4.3, 110, 116, 6%)

In the above table, his lifestyle is "low-carbs and high-exercise" with his sensor PPG around 6% higher than his finger PPG.

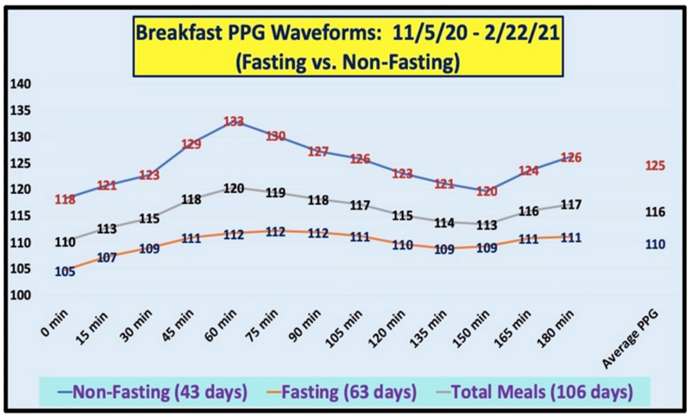

Figure 1: Breakfast PPG waveforms of fasting, non-fasting, and total breakfasts (11/5/2020 - 2/22/2021)

Frequency Domain of PPG Wave

He utilized the Fast Fourier Transform (FFT) algorithm-based software program to convert his PPG waves from a time-domain into a frequency-domain. It is interesting to notice that the average Y-amplitudes of frequency domain are 85 for fasting and 72 for non-fasting which is the reversed order of Y-amplitudes of time domain, i.e., 110 mg/dL for fasting PPG and 125 mg/dL PPG for non-fasting PPG.

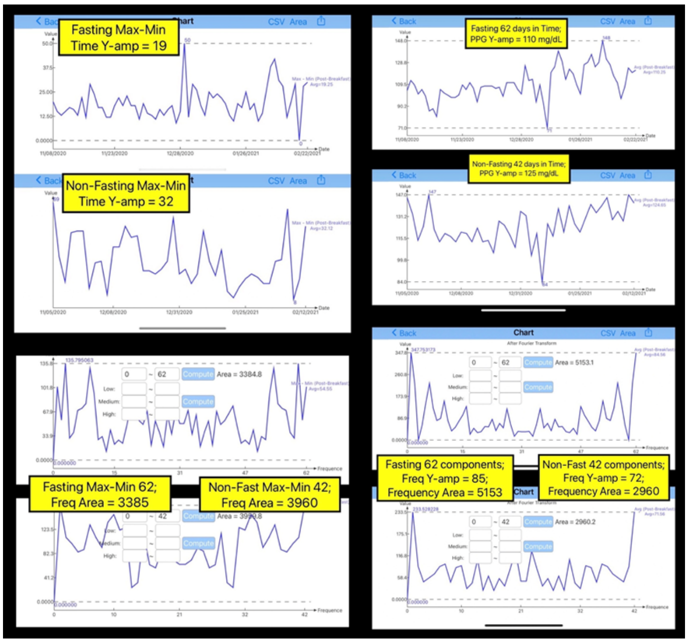

Figure 2: PPG wave and PPG fluctuations (GV) including both Time domain and Frequency domain of fasting and non- fasting (11/5/2020 - 2/22/2021)

Furthermore, he utilizes three methods to calculate the estimated relative energy levels associated with glucose waves and glucose fluctuations, respectively.

(1) He calculates the total area underneath the curve in frequency domain or the "frequency area", using a computer. He obtains the following two relative energies:

Fasting 5153
Non-fasting 2960

(2) He uses the average Y-amplitude value in frequency domain to multiply the number of components or segments N, by hand. He obtains the following two relative energies:

Fasting 5243
Non-fasting 3006

The results from Method 2 is very close to Method 1, since they have the same equation to calculate relative energy, but one using a computer (more accurate) and the other using hand calculation (less precise).

(3) He uses the square of Y-amplitude slur in time-domain (i.e., average PPG value) to estimate the relative energy associated with PPG wave. Since the values of N are different between fasting (62) and non-fasting (42); therefore, he also multiplies the squared PPG value by a ratio of either (fasting days / total days) or (non-fasting days / total days). It is noted that all three different methods have yield similar data patterns of relative

energy between fasting PPG (bigger energy) versus non-fasting PPG (smaller energy).

(11/5/2020 - 2/22/2021)	Fasting Breakfast	Non-Fasting Breakfast	Total Breakfast
No. of Meals	63	43	106
Avg. PPG (Finger)	105.8	115.2	109.6
Carbs/Sugar grams	0.0	7.5	3.0
Post-meal Walking Steps	4183	4367	4258
No. of components (N: Days or Frequencies)	62	42	105
Avg. PPG (Time-Domain Y)	110	125	116
Avg. amplitude (Frequency Domain Y)	85	72	122
(1) Frequey Area	5,153	2,960	12,732
(2) Freq-Y * N	5,243	3,006	12,854
(3) Time-Y **2 * (N ratio)	7,177	6,215	13,477
No. of components (N: Days or Frequencies)	62	42	105
K-line PPG Max	120.5	142.3	129.3
K-line PPG Min	101.2	110.2	104.9
K-line Max-Min	19	32	24
Avg. Max-Min of PPG (Time-Domain Y)	20	32	25
Avg. amplitude (Frequency Domain Y)	55	94	120
(1) Frequey Area	3,385	3,960	12,648
(2) Freq-Y * N	3,382	3,948	12,563
(3) Time-Y **2 * N *(N ratio)	14,208	17,332	64,267
(Max-Min) / Avg. PPG	18%	26%	21%

Figure 3: demonstrates a complete data table containing both input data and calculated results from time domain and frequency domain.

PPG Fluctuation in Time Domain

He defines his PPG fluctuation (a similar concept to GV) as the maximum PPG value minus the minimum PPG value. He utilizes the Candlestick K-line model to obtain his maximum and minimum values of PPG, instead of obtaining them from a synthesized PPG wave. When 42 days or 62 days of PPG data being synthesized into a final waveform, the "absolute and real" data scale of the individual day's peak and nadir would be lost in the process. He obtains the following PPG fluctuation (i.e., Max - Min):

Fasting 20
Non-fasting 32

It should be pointed out that the non-fasting fluctuation has 12 mg/dL (or 60%) higher than the fasting fluctuation.

PPG Fluctuation in Frequency Domain

Again, he applies the FFT algorithm to convert these PPG fluctuation waves into frequency domain and the same three energy calculation models to obtain the relative energies associated with the PPG fluctuations. By using Method 1 of frequency area, he obtains the following relative energies:

Fasting 3385
Non-fasting 3382

However, by using Method 2 of the average Y-amplitude of frequency domain multiplying N, he obtains the following relative energies:

Fasting 3960
Non-fasting 3948

For the PPG fluctuation case, the relative energy level associated with PPG fluctuations of both Method 1 and Method 2 are remarkably close to each other. However, the non-fasting energy of fluctuation is only slightly higher than the fasting fluctuation.

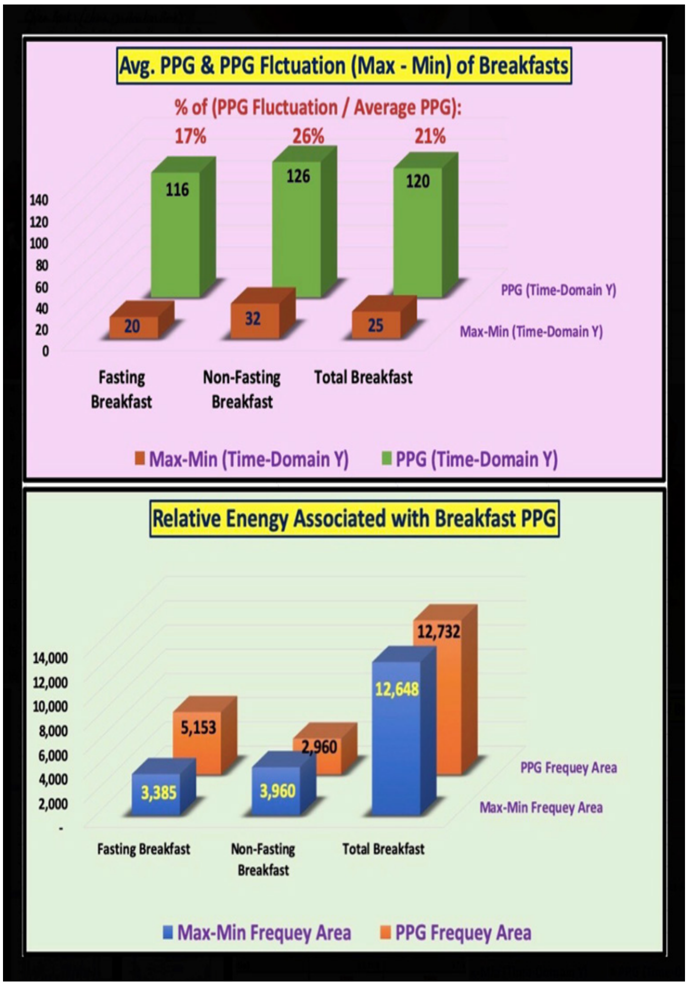

Figure 4: reveals the combined results in a bar diagram with the upper portion for time domain and the lower portion for frequency domain.

Conclusions

In summary, from the time domain analysis, the non-fasting's average PPG value is 15 mg/dL, which is 14% higher than the fasting's average PPG; and the non-fasting's peak PPG value is 21 mg/dL, which is 19% higher than the fasting's peak PPG value. Even the PPG wave fluctuations (Max.-Min.) of the non-fasting is 12 mg/dL, which is 60% higher than the fasting. It is interesting to observe that the fasting glucose wave still has fluctuations even though it is much "calmer".

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(4) The relative energy associated with PPG wave fluctuations

reflects that non-fasting is 17% higher than fasting which is due to the difference of 12 mg/dL, which is 60% of PPG fluctuation (Max - Min) in time domain. Besides, the Fourier Transform operation did not change the PPG fluctuation's characteristics in its frequency domain.

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