ISSN: 2640-4133

Research Article

Advances in Bioengineering & Biomedical Science Research

Using Three Analysis Methods: Time-Series, Spatial, And Frequency-Domain to Analyze and Forecast Key Diabetes Biomedical Variables (GH-Method: Math-Physical Medicine)

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Submitted: 23 Apr 2020; **Accepted**: 30 May 2020; **Published**: 26 May 2020

Introduction

This paper describes the author's application of Time-Series Analysis, Spatial Analysis, and Frequency-Domain Analysis (including wave theory, Candlestick charting, segmentation pattern analysis) to analyze and forecast certain biomedical key variables of type 2 diabetes (T2D) conditions. The dataset is provided by the author, who uses his own type 2 diabetes metabolic conditions control, as a case study via the "math-physical medicine" approach of a non-traditional methodology in medical research.

Math-physical medicine (MPM) starts with the observation of the human body's physical phenomena (not biological or chemical characteristics), collecting elements of the disease related data (preferring big data), utilizing applicable engineering modeling techniques, developing appropriate mathematical equations (not just statistical analysis), and finally predicting the direction of the development and control mechanism of the disease.

Method

The author was diagnosed with type 2 diabetes in 1995. He has measured his Finger glucoses four times a day since 2012. He has stored his 10,760 Finger glucoses data of 7.5 years or 2,690 days on a cloud server. On 5/5/2018, he applied a Sensor on his upper arm to collect 27,448 glucose data (376 days from 5/5/2017 to 5/15/2019 with 73 data per day).

He utilizes the GH-Method: math-physical medicine to manage metabolic disorder diseases especially diabetes. Initially, he observed various disease phenomena and recorded big volume of related data. Based on this big dataset, various key variable's patterns and their moving trends can be observed and analyzed through further mathematical and statistical operations, including suitable computational tools, including time-series analysis, spatial analysis, frequency-domain analysis, and artificial intelligence. Finally, he utilized his acquired medical domain knowledge to link his mathematical results with suitable biomedical interpretations in order to discover some hidden facts and their potential dangers to his health.

In this paper, he disregards the theoretical discussion of those applied mathematical methods in order to focus on application with his diabetes research results.

In frequency-domain analysis, he applied the wave theory and Fourier Transform to convert the glucose waveforms from time-domain (Time) into frequency-domain (Frequency).

He defined three key variables for frequency-domain analysis results:
GT - glucose in Time
G2 - glucose square
AF - Amplitude in Frequency

Results

Here are some of the results from three specific analysis and forecasting models:

(A) Time-Series Analysis

• **(A1) Weight:** He developed a weight prediction model based on food portion, exercise, and certain metabolism aspects and achieved 99.8% linear accuracy with a correlation coefficient (R) of 90% to compare with actual weight. Weight contributes ~85% of Fasting plasma glucose (FPG) formation.

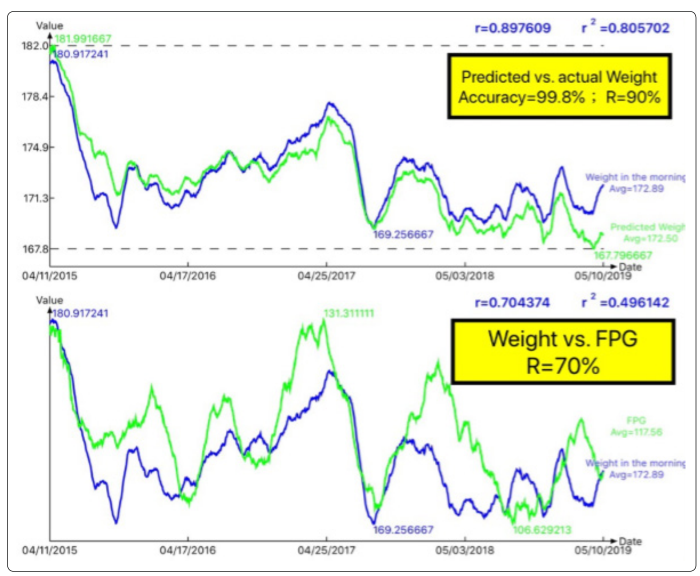

Figure A1: Weight and FPG

• **(A2) FPG in early morning:** Using time-series analysis, he obtained R=70% between weight and FPG.

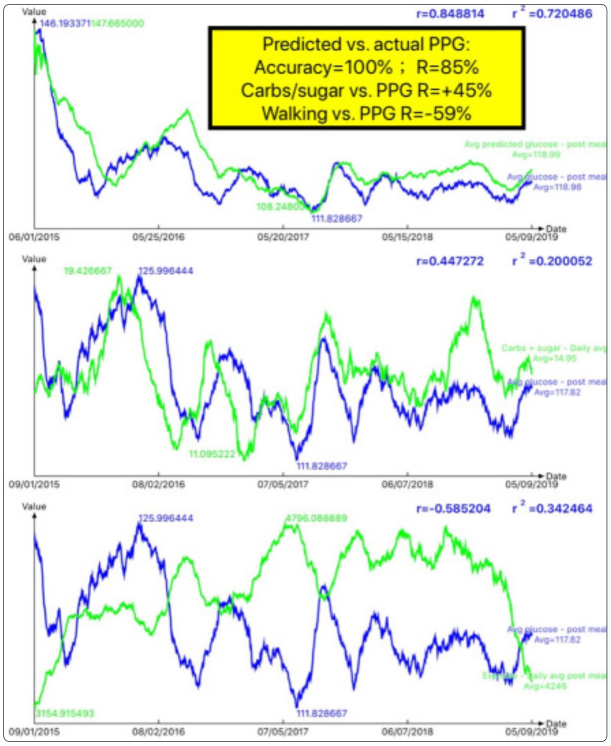

Figure A2: Carbs/sugar (+R) and Walking (-R) vs. PPG

• **(A3) Postprandial plasma glucose (PPG) measured at two hours after fist-bite of meal:** Using time-series analysis, he obtained R= +45% between carbs/sugar intake and PPG and R= -59% between post-meal walking and PPG. Combined carbs/sugar and walking contributes ~80% of PPG formation. He also achieved 100% linear accuracy and R=85% between predicted and actual PPG.

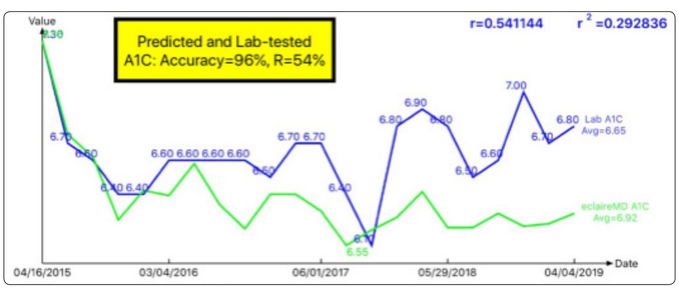

Figure A3: HbA1C

• **(A4) Hemoglobin A1C or HbA1C (A1C):** The medical community uses A1C as the measuring yardstick to determine the severity of the patients' diabetes conditions. There are no consistent or uniform conversion ratios available between glucose and A1C values. Therefore, the author applied statistics tools (including time-series analysis, spatial analysis, and frequency-domain analysis) and engineering approximation modeling to build an effective mathematical A1C forecasting model. Using time-series method, in comparison of this mathematically forecasted A1C results and lab tested biological A1C results (quarterly measured data due to medical insurance constraints), he achieved a linear accuracy of 96% and R=54%.

(B) Spatial Analysis

• **(B1) Weight:** The orientation of data cloud with predicted and measured weight values are skewed from lower right toward upper left. The values of predicted weight and actual weight are very close to each other and move together simultaneously. This reflects high accuracy and correlation between these two variables.

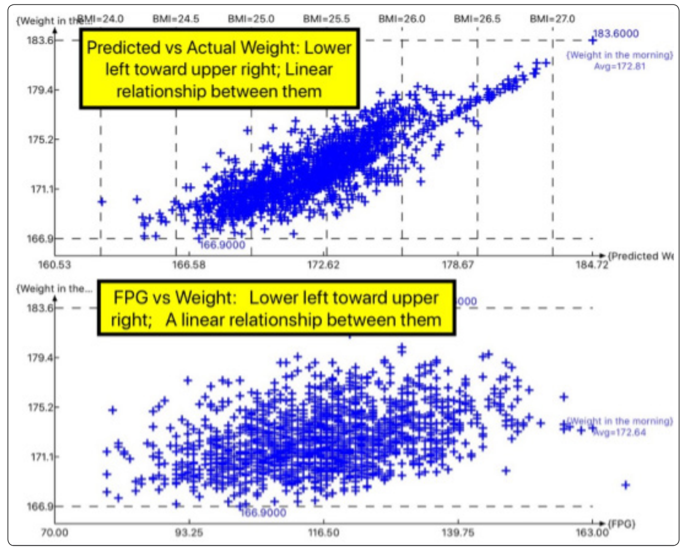

Figure B1: Weight and FPG

• **(B2) FPG in early morning:** The orientation of data band of FPG vs. Weight is also from lower left toward upper right. This means that they are closely correlated and weight is the major formation factor of FPG.

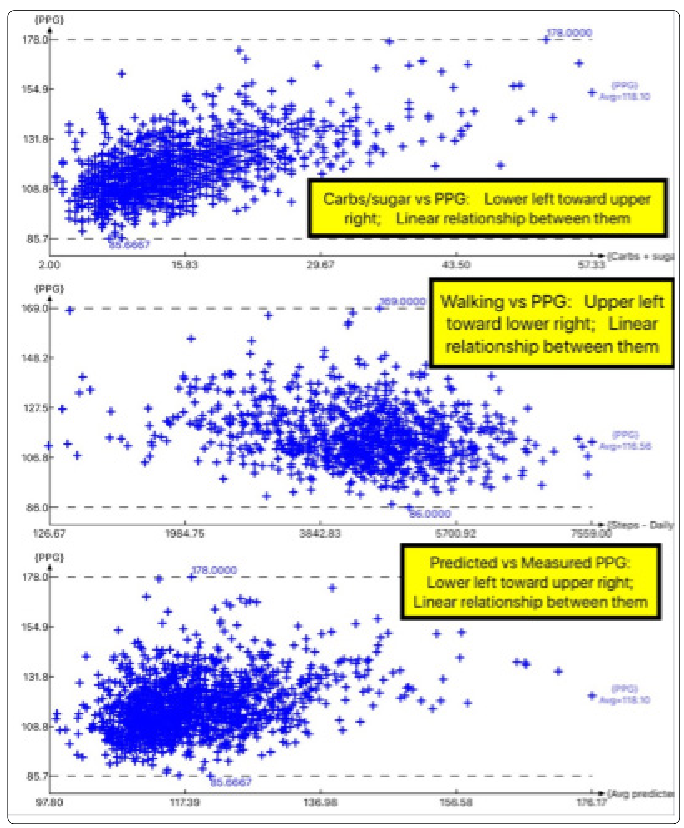

Figure B2: Carbs/sugar (+R) and Walking (-R) vs. PPG

• **(B3) PPG at two hours after fist-bite of meal:** The orientation of data band of carbs/sugar vs. PPG is from lower left toward upper right (positive) which means more carbs/sugar creates higher PPG. However, the orientation of data band of post-meal walking vs. PPG is from upper left toward lower right (negative) which means more walking steps brings down PPG.

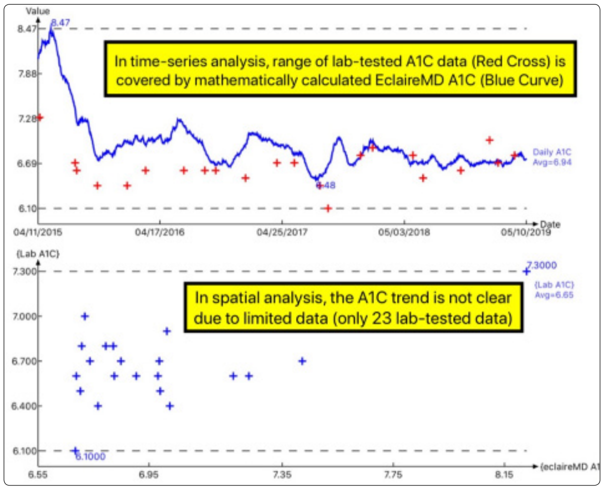

Figure B3: HbA1C

• **(B4) Hemoglobin A1C or HbA1C (A1C):** Using spatial analysis to compare mathematically predicted A1C and lab-tested biological A1C (quarterly tested data due to insurance constraints), he noticed that spatial analysis tool is not as effective as time-series analysis tool due to limited lab-tested A1C (only 23 data). One limitation about spatial analysis is the requirement of a larger size of data in order to see the patterns and trends of data movement clearly.

(C) Frequency-Domain Analysis

• (C1) The highest glucoses in Time (GT) are corresponding to the lowest amplitudes in Frequency (AF). The same observation holds true for both FPG and PPG data diagrams.

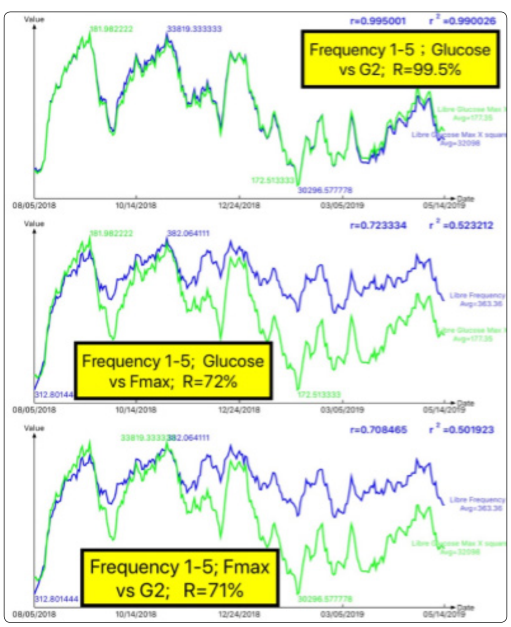

Figure C1: Correlation Coefficient of Glucose, Glucose Square, and Frequency Amplitude

Frequency Range	0 - 1	0 - 5	0 - 10	0 - 15
Highest Glucose in Time (mg/dL)	187	176	168	162
Relative Energy (by averaged Glucose Square)	35962	31772	28640	26542
Relative Energy (Highest Amplitude in Frequency)	577	403	280	215
Data Period (5/5/2018 - 5/15/2019 @ 73 data per day)				
Calculation 1 (Glucose Square Value)	34969	30976	28224	26244
Calculation 2 (Glucose Square's Accuracy)	97%	97%	99%	99%
Energy Ratio (Glucose Square / Frequency Amplitude)	62	79	102	123
Frequency to Time Ratio (Frequency Amplitude / Highest Glucose)	3.1	2.3	1.7	1.3
Calculation 3 (Energy Ratio * Frequency to Time Ratio)	192	181	170	164
Calculation 4 (Inverse to Glucose's accuracy: Glucose in Time / Calculation 3)	97%	97%	99%	99%

Relative energy associated with amplitude in frequency domain analysis (converted from high glucoses in time-domain analysis via Fourier Transform)

Table C1: Segmented Frequency Amplitude Analysis and Sime Calculations

• (C2) According to physics, the energy associated with a wave is directly proportional to the square of the wave's amplitude. Through the results of having three pairs of high existing triangular correlation coefficients, it proves that the amplitude in Frequency-domain is indeed the "relative" energy level of glucose in Time-domain (see Figure C1: 99.5% between GT and G2; 72.3% between GT and AF; and 70.8% between G2 and AF).

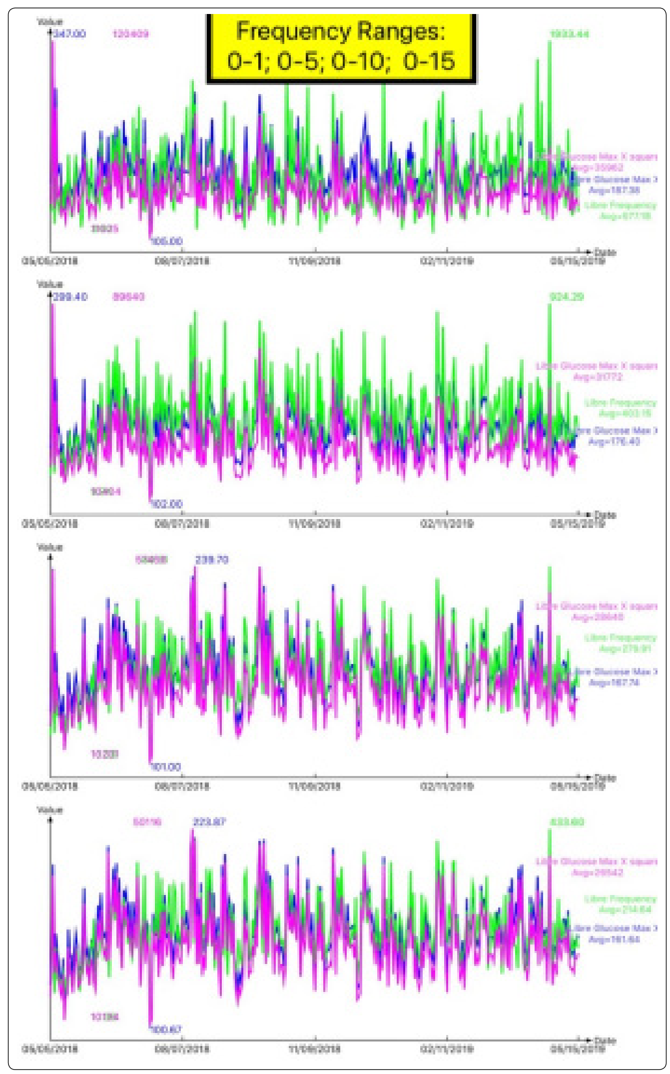

Figure C2: Four Segmented Frequency Range Groups

• (C3) The author further segmented the glucose and frequency data into four groups with different frequency ranges: 0-1, 0-5, 0-10, and 0-15. Through this frequency segmentation pattern analysis (Figure C2) of GT, G2, and AF, the more inclusion of lower amplitude of glucose values in a particular segmented group causes their corresponding frequency value to increase; however, their associate averaged energy level of this group would decrease.

Conclusion

By using both time-series analysis and spatial analysis methods, this clinical case study with different mathematical tools of more than four years, encompassing 1,488 days and ~500,000 big data, has demonstrated their powerful analyzing and forecasting capabilities on understanding key biomedical variables, e.g. weight, glucose, and diabetes control.

Furthermore, the author's research work has also proved the amplitude (y-axis value of frequency-domain) is associated with relative energy level carried by the glucose (y-axis value of time-domain). Glucose-carried energy is circulating inside the human body to provide the needed energy for activities. However, when "excessive" energy associates with "high" glucose in circulation, they will damage the internal organs as well, i.e. diabetes induced complications such as CVD, stroke, foot ulcer, renal and retinal problems. This quantitative analysis not only provides mathematical proof of detailed biomedical phenomena but also offers extra tools for estimating the risk probabilities of various diabetes complications [1-4].

References

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