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Time-Series Data Analysis of Blood-Sugar Level of a Diabetic in Relationship to Lifestyle Events

Hiroshi Takeuchi, *Senior Member*, *IEEE*, Naoki Kodama, and Katsunori Tsurumi

Abstract— **Twelve days of time-series blood-sugar level data of a diabetic were analyzed in relationship to lifestyle events such as food ingestion, alcohol intake, and exercise. In this analysis, to exclude the influence of other lifestyle events on blood-sugar level variation, only data within time -windows where the target lifestyle event occurred, were considered. Three main results were obtained: (1) ingestion of grain or meat/fish/beans caused blood-sugar level to peak after one hour, (2) exercise decreased blood-sugar level rapidly in thirty minutes, (3) alcohol intake, particularly beer, increased blood-sugar level.**

I. Introduction

A health-check system for protection against metabolic syndrome started in 2008 in Japan. In this new system, checking one's health based on medical data that specifies the relationship between personal lifestyle and health data is very important. Previously, we analyzed the influence of lifestyles (mainly diet) to blood-sugar (glucose) and HbA1c levels based on daily time-series data of a diabetic taken over about four years. We extracted association rules among lifestyle events, blood-sugar level, and HbA1c level of a diabetic [1]. Generally speaking, blood-sugar level is difficult to manage for many people with diabetes, since it is affected in a complex and non-linear manner by carbohydrate intake, medication, and exercise. Thus, computer-based decision support systems on this subject have been proposed [2 -4].

In this study, we dynamically analyzed a diabetic's blood-sugar level time-series data every thirty minutes over twelve days in relationship to lifestyle events such as ingestion, alcoholic intake, and exercise. In this analysis, to exclude the influence of non-target lifestyle events on blood-sugar level, only data within time -windows where the target lifestyle events occurred, were considered.

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Hiroshi Takeuchi is with the Department of Healthcare Informatics, Takasaki University of Health and Welfare, 37-1, Nakaorui-machi, Takasaki-shi, Gunma, 370-0033, Japan (phone: +81-27-352-1290; fax: +81-27-353-2055; e-mail: htakeuchi@ takasaki-u.ac.jp).

Naoki Kodama is with the Department of Healthcare Informatics, Takasaki University of Health and Welfare, 37-1, Nakaorui-machi, Takasaki-shi, Gunma, 370-0033, Japan (e-mail: kodama@takasaki-u.ac.jp).

Katsunori Tsurumi is with the Department of Health & Nutrition, Takasaki University of Health and Welfare, 37-1, Nakaorui-machi, Takasaki-shi, Gunma, 370-0033, Japan (e-mail: tsurumi@takasaki-u.ac.jp).

II. Materials and Methods

A. Analysis Model

The time-series data analysis described here is based on the simple idea that the accumulation of the effects of lifestyle events such as ingestion, alcohol intake, and exercise could affect personal health condition with some delay [5 -7]. The delay may reflect complex bio-reactions such as those of metabolism in a human body. In the analysis, the accumulation of the effects of lifestyle events is represented by a summation of energy supply or expenditure data (calorie) due to ingestion, exercise, etc. The accumulation of the effects may cause variation of health data such as body-mass-index, body-fat percentage, and blood-sugar level with some delay.

B. Acquisition of Time-Series Data

Time-series data of blood-sugar level and lifestyle events were obtained from a type-2 diabetic 45-year-old male whose BMI is 18.5. Blood-sugar level was measured as many times as possible while awake (including working time) using a glucose self-monitoring device (Arkley, Kyoto, Japan). Data were taken 178 times over twelve days.

Ingestion, alcohol intake, and energy expenditure due to exercise were recorded every time these events occurred. Ingestion in kcal was grouped into five food categories: grain, vegetable, fruit/confectionary, dairy products, and meat/fish/beans. Kcal were estimated from each day's breakfast, lunch, and dinner content using a "shokusai-seikatsu" (Tanita software). Alcohol intake in kcal was recorded in three categories: beer, wine, and distilled liquor. Energy expenditure due to exercise was measured with a wearable "intelligent calorie counter"device (IT Research, Inc., Japan).

C. Data Processing

Data processing is shown in Fig. 1 (a), where e is the lifestyle event data and h is the blood-sugar level data. Here, h_n is the value of h at time n, and e_i is the value of e at time i. The time interval was thirty minutes. Assuming that lifestyle event data affects blood sugar level with some delay, we define a retardation parameter s as ($s = n - i$). Further, the quantities Δh_{nm} and e_{ij}^t are defined as follows:

$$\Delta h_{nm} = h_n - h_m \quad (1)$$

$$e_{ij}^t = e_i + e_{i-1} + ... + e_j \quad (2)$$

Then the correlation between Δh_{nm} and e^t_{ij} in time-series data is examined by changing $n-m$, $i-j$, and s as parameters and calculating Pearson's product-moment correlation coefficient r_{he} for each $(n-m, i-j, s)$ set. Here,

$$r_{he} = S_{he} / (S_h \cdot S_e), \qquad (3)$$

where S_{he} is the covariance, and S_h and S_e are the standard deviation of Δh_{nm} and e^t_{ij}, respectively. Conceptual scatter plots between Δh_{nm} (variation of blood-sugar level) and e^t_{ij} (summation of lifestyle event data) are shown in Fig. 1 (b). The condition where r_{he} becomes largest is searched for in the time-series data. The correlation coefficient, r_{he}, typically changes with $(n-m, i-j, s)$ set as shown in Fig. 1 (c). Finally, the maximum value of r_{he} is tested for correlation significance.

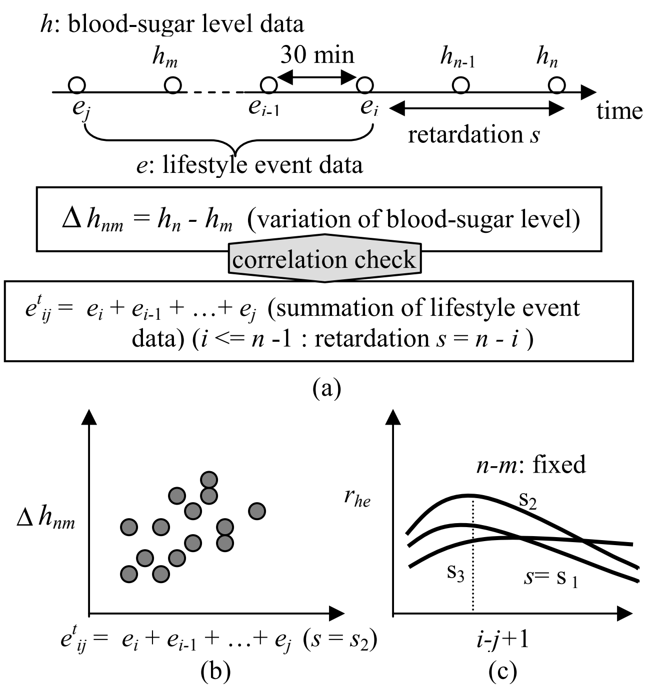

Fig. 1 Processing of time-series data

III. Results

A. Time-Series Variation of Blood-Sugar Level

Blood-sugar level variation (thirty- minutes interval time-series data) for twelve days is shown in Fig. 2. In the figure, we interpolated data because actual data were not necessarily taken every thirty minutes. There were 178 actual data points and 371 interpolated data points. Since the data included samples of immediately after meals, the values varied greatly from 60 mg/dl to over 300 mg/dl.

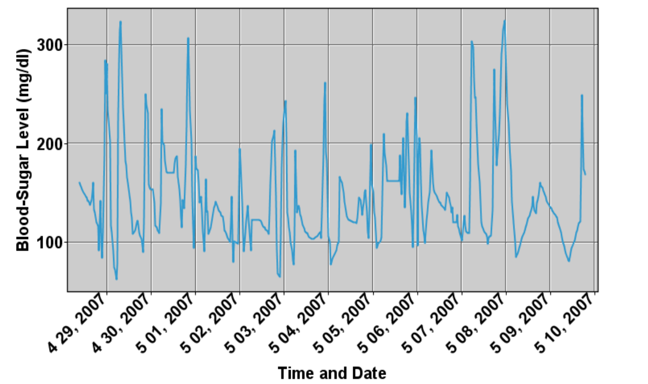

Fig. 2 Time-series blood-sugar level data for twelve days (178 actual data points and 371 interpolated data points)

B. Actual Data Analysis

The purpose of the analysis was to find out how lifestyle events such as food ingestion, alcohol intake, and exercise dynamically affect blood-sugar level. However, each lifestyle event occurred during only a small part of the total time over the twelve -day monitoring period. Thus, we analyzed only time-series blood-sugar level data within time -windows where the target lifestyle event occurred. The method is described in Fig. 3.

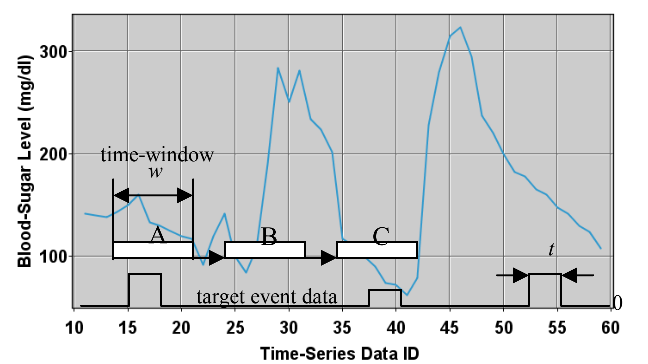

Fig. 3 Definition of time-window and target blood-sugar level data (section A and C: target areas, section B: out of target area)

The width of time-window, w, was typically set to two times the amount of time that the target event took, t. If there were no target events in a window, as in section B in Fig. 3, the corresponding time-series blood-sugar level data were omitted in the analysis. With this method, the influences of lifestyle events other than the target event could be largely reduced.

C. Effects of Ingestion

Ingestion of grain and meat/fish/beans mostly correlated to increase in blood-sugar level as shown in Figs. 4 and 5. In the figures, the number after "Blood-Sugar Level Variation" represents the interval of variation, n-m (Fig. 1 (a)). That is, "Blood-Sugar Level Variation 4" means variation of blood-sugar level compared to 2 hours earlier. The number

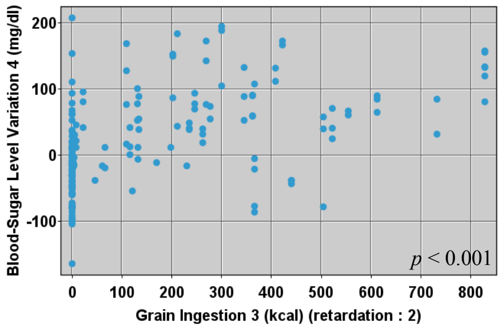

Fig. 4 Scatter plots of blood-sugar level variation vs. grain ingestion ($w = 6$ (3 hours), $n = 187$, and $r = 0.491$)

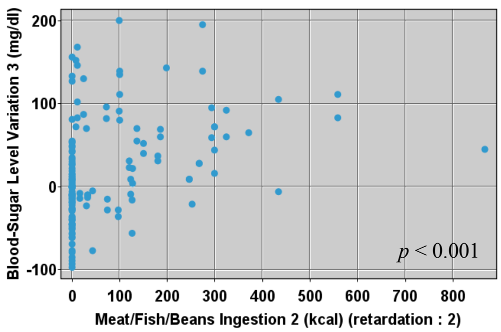

Fig. 5 Scatter plots of blood-sugar level variation vs. meat/fish/beans ingestion ($w = 5$ (2.5 hours), $n = 150$, and $r = 0.349$)

after "Ingestion" represents summation number of the data, $i - j + 1$ (Fig. 1 (a)). That is, "Grain Ingestion 3" means total grain ingestion for 1.5 hours. Also, "retardation : 2" means $s = 2$ (1 hour) (Fig. 1 (a)). In the figure captions, w is the width of the time-window, n is the number of data points, and r is Pearson's correlation coefficient.

Since correlation coefficients became largest when $s = 2$ (1 hour) in both cases, increase in the blood-sugar level due to grain or meat/fish/beans ingestion may peak after about one hour. No significant correlation was observed in other food categories in this study.

D. *Effect of Exercise*

Scatter plots between blood-sugar level variation and energy expenditure due to exercise are shown in two ways in Figs. 6 and 7. The only difference is in the retardation parameter.

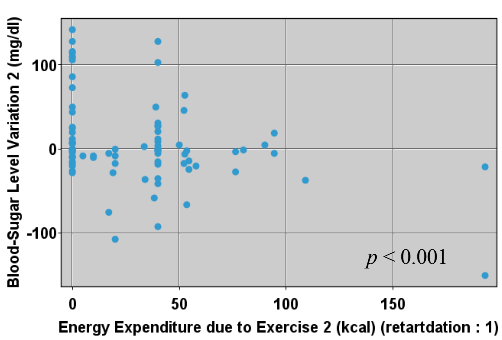

Fig. 6 Scatter plots of blood-sugar level variation vs. energy expenditure due to exercise ($w = 4$ (2 hours), $n = 85$, and $r = -0.368$)

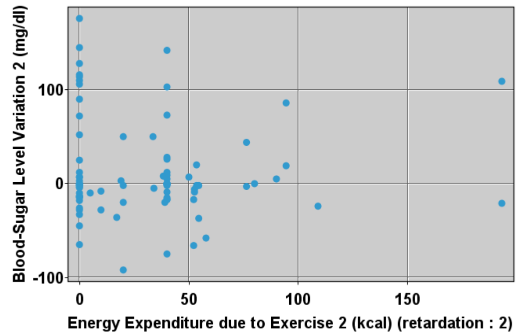

Fig. 7 Scatter plots of blood-sugar level variation vs. energy expenditure due to exercise ($w = 4$ (2 hours), $n = 85$, and $r = -0.030$)

For retardation $s = 1$ (30 min), a significant negative correlation between blood-sugar level variation and energy expenditure due to exercise was observed (Fig.6). For retardation $s = 2$ (one hour), however, no correlation was observed (Fig.7).

This result may indicate that the effect of exercise is rapid and decrease in the blood-sugar level peaks within 30 min after exercise.

E. *Effects of Alcohol Intake*

Generally speaking, alcohol is not good for people with diabetes. The diabetic in question, however, drinks alcohol (mainly, beer and distilled liquor) restrictively. As shown in Fig. 8, alcohol intake increased blood-sugar level within 30 min after drinking.

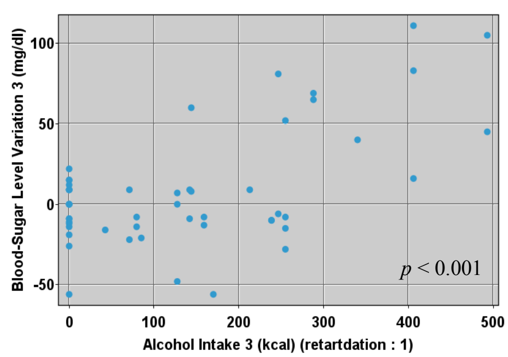

Fig. 8 Scatter plots of blood-sugar level vs. alcohol intake ($w = 6$ (3 hours), $n = 51$, and $r = 0.590$)

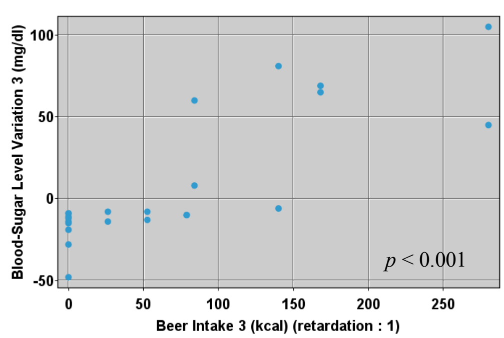

Fig. 9 Scatter plots of blood-sugar level vs. beer intake ($w = 6$ (3 hours), $n = 23$, and $r = 0.821$)

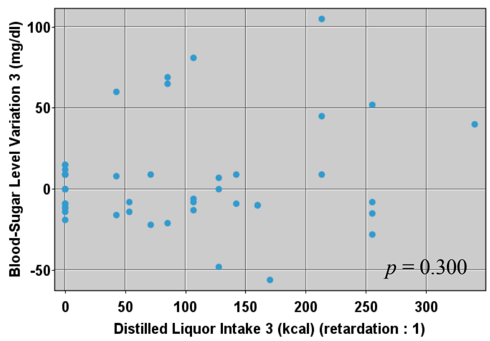

Fig. 10 Scatter plots of blood-sugar level vs. distilled liquor intake (w = 6 (3 hours), n = 45, r = 0.158)

Interesting results were obtained by further analyzing the effect of alcohol intake. Figure 9 is a scatter plots of blood-sugar level variation against beer intake. A strong correlation was observed. However, no significant correlation was observed between blood-sugar level variation and distilled liquor intake (Fig. 10). These results suggest that the increase in blood-sugar level was mainly due to beer intake.

IV. Discussion

A. Data Analysis Method

We have reported time-series data analysis method based on collecting both health and lifestyle data daily [5 -7]. We have extracted some useful rules among lifestyles and daily health conditions using the method.

In this study, blood-sugar level data were analyzed in relationship to lifestyle events every thirty minutes. Since each lifestyle event, such as ingestion and exercise, occurred irregularly during only a small part of the total time over twelve days, we introduced a time-window concept for the analysis. If there were no data about the target lifestyle event within the time-window, blood-sugar level data in the corresponding area were omitted in the analysis. The width of time-window, w, was typically set to $2t$, where t is the amount of time that the target event took..

This method was found to be effective for reducing noise in the correlation analysis. That is, the influence of lifestyle events other than the target events was reduced.

B. Results of Analysis

Previous long-term time-series data analysis indicated that daily excess ingestion of grain and meat/fish/beans increased fasting plasma glucose and HbA1c levels of the diabetic in question [1]. In this study, also, ingestion of these two food categories was found to significantly correlate to increase in the blood-sugar level after meals. Accumulation of this effect could cause an increase in fasting plasma glucose and HbA1c levels.

Previous long-term analysis also indicated that daily exercise significantly decreased HbA1c level [1]. In this study, exercise was found to decrease the blood-sugar level rapidly (within 30 min).

For alcohol intake, which is generally restricted in diabetics, long-term analysis implied that regular and moderate distilled liquor intake decreased HbA1c level of the diabetic in question [1]. In this study, alcohol intake was found to significantly increase the blood-sugar level. The increase in the blood-sugar level was mainly due to beer intake. No significant correlation between blood-sugar level variation and distilled liquor intake was observed.

V. Conclusion

Time-series blood-sugar level data of a diabetic were analyzed every thirty minutes over twelve days in relationship to lifestyle events. The method of analysis was based on the simple idea that the accumulation of the effects of lifestyle events could affect blood-sugar level with some delay. A time-window concept was introduced to reduce noise in the correlation analysis.

The following results were obtained:

(1) Ingestion of grain or meat/fish/beans increased blood-sugar level with a peak after about one hour.

(2) Exercise decreased blood-sugar level rapidly, with-in thirty minutes.

(3) Alcohol intake, particularly beer intake, increased blood-sugar level.

It should be noted, however, that these results can not be generalized since the algorithm presented here was evaluated on only one subject. Also, evaluation of these results in the medical aspect is remained.

Acknowledgment

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References

[1] H. Takeuchi, M. Ishikawa, and N. Kodama, "Time-series data analysis of blood sugar and HbA1c levels of diabetic," *Proc. 4th Int. Conf on Advances in Medical, Signal, and Information Processing*, 2008, P1.7.

[2] E. D. Lehmann and T. Deutsch, "Applications of computers in diabetes care – a review Computers for decision support and education," *Med. Inform*., 20(4), 1995, pp.303 -329.

[3] E. D. Lehmann (Editor), "Application of information technology in clinical diabetes care," Special Issues of *Medical Informatics*, 21(4), 1996, pp. 255 -378.

[4] W. A. Sandham, E. D. Lehmann, D. J. Hamilton, and M. L. Sandilands, "Diabetes management and education using blood glucose simulation software," *Proc. IET Int. Technical Symposium Improved Diabetes Healthcare: The Impact of Advanced Engineering and Technology*, 2008, pp. 1 -4.

[5] H. Takeuchi, N. Kodama, T. Hashiguchi, and N. Mitsui, "Healthcare data mining based on a personal dynamic healthcare system," *Proc. 2nd Int. Conf. on Computational Intelligence in Medicine and Healthcare,* 2005, pp. 37 -43.

[6] H. Takeuchi, N. Kodama, T. Hashiguchi, and D. Hayashi, "Automated healthcare data mining based on a personal dynamic healthcare system," *Proc. 28th IEEE EMBS Annual Int. Conf.* 2006, pp.3604 -3607.

[7] H. Takeuchi, Y. Ikeda, and N. Kodama, "Time-series data analyses for healthcare-data-mining based on a personal dynamic healthcare system," *Proc. 12th World Congress on Medical Informatics* (MEDINFO), 2007, P309.