

Tracking of Monthly Health Condition Change from Daily Measurement of Systolic Blood Pressure

Wenxi Chen¹ and Toshiyo Tamura²

¹Biomedical Information Technology Lab., CAIST, The University of Aizu, Tsuruga, Aizu-wakamatsu 965-8580, Japan

²Faculty of Biomedical Engineering, Osaka Electro-Communication University, Shijonawate, Osaka 575-0063, Japan

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Abstract: This paper presents an approach to detect monthly biorhythmic change using daily measurement of systolic blood pressure (SBP) at home. As a part of health promotion campaign initiated in 1994, more than 600 households in West Aizu village of northern Japan were provided devices for daily measurement of blood pressure, electrocardiogram, body temperature and body weight. This paper demonstrates an outcome of data analysis of daily SBP collected in two years from an elder couple at age of seventies. The personal reference profile is gained by averaging individual monthly profiles over 24 months. Dynamic time warping algorithm estimates the similarity between personal reference profile and monthly SBP profile. The results show that an extraordinary deviation from usual biorhythmicity can be found in both the wife and the husband happened in July and February which respectively indicates individual health condition change confirmed by personal medical record. The results suggest that even it is difficult to identify any significant variation from the daily SBP directly, proper analysis of the raw SBP measured over a long-term period helps tracking functional information of health condition change and serving as an effective evidence for health management.

1 INTRODUCTION

Flood of information brings a big impact on the way we live and work. Every day, 2.5 quintillion bytes of data are being generated, and so much that 90% of the data in the world today have been created in the last two years alone (IBM Corp., 2011). These data come from everywhere such as sensors, posts, pictures and videos, transaction records and personal information. Increase in quantity philosophically will lead to profound change in quality. The vast amount of data is more than simply a matter of size, and sometimes is likely a double-edged sword. It usually has a huge reserve of latent information but often blurs the focus of the interests.

It is crucially an important challenge in exploring proper approaches to handle these data and to mine functional information from daily accumulated such kind of data, and ultimately to discover structural knowledge for real world application (Zins, 2007).

Detection of influenza epidemics using only search engine query data announced the arrival of the Big Data age and paved the way for finding new

value from multiple disciplines (Ginsberg et al., 2008).

Diversified devices were developed to acquire multifarious physiological data under daily life environment conveniently. Variety of algorithms were devised to reveal the relationship between data features and physiological signatures in healthcare domain.

West Aizu village, located in northern Japan and about 300 km away from Tokyo, had pioneered the "Challenge to 100 years of age" project since 1994. The project had been supported by various financial resources of total 2.4 billion Japanese Yen, and established its fundamental goal to promote healthier life by providing a total care solution package to villagers (West Aizu, 2003). The village built a cable television network infrastructure, improved the soil for the cultivation of crops, enhanced educational programs on the importance of a nutritionally balanced diet and good lifestyle practice, and initiated a health promotion campaign. Special tailor-made devices were distributed to 687 households among total 2,819 families in the village. Daily physiological data are measured by

participants at home and transmitted from home to the healthcare centre via the cable network.

This paper is to explore a feasible way to harvest such kind of daily data accumulated over a long-term period, and to find structural and functional information which can be linked to health condition change.

2 METHOD AND MATERIAL

2.1 Data Collection

The tailor-made device can measure systolic blood pressure (SBP), diastolic blood pressure (DBP), body temperature (BT), body weight (BW), one-minute electrocardiogram (ECG) and heart rate (HR) profile, and also collect answers to a daily questionnaire displaying on a LCD screen after completion of daily measurement. Measured data are transmitted to the healthcare centre by home network connection and accumulated in the database server of the centre. The time of the daily measurement is not strictly stipulated: preference of the morning or the afternoon is at the disposal of the participants. Seven nurses are in charge of the data review and respond to inquiries from the participants. Biochemical markers from blood and urine samples are also collected in yearly regular health check-up.

The participants involved in the project were given the explanation on the study purpose and the daily tasks, and were asked to sign an agreement prior to the data collection.



Figure 1: Snapshot in measurement of blood pressure using the device at home. The measured data were transmitted to a database server via a village network connection.

Figure 1 shows a housewife measuring the blood pressure at home by the device. Three large buttons “Yes”, “No”, “Return” and a speaker for voice guidance are designed especially for elders to manipulate more easily.

Figure 2 shows daily measurements of SBP, DBP, HR, BT and BW in two years from an elder couple; upper and lower plots indicate the wife and husband, respectively. The wife was born in 1925 and suffered from hypertension and had accepted coronary artery bypass grafting surgery. The husband was born in 1924 and had no overt symptoms.

It is observable that the physiological data in the wife demonstrates the wax and wane corresponding to the temporal ebb and flow. SBP, DBP and HR tend to decline in the summer and rise in the winter. However, the biorhythmicity in the husband shows an obscure pattern. The polynomial fitted curves (brown lines) for the SBP show that individual

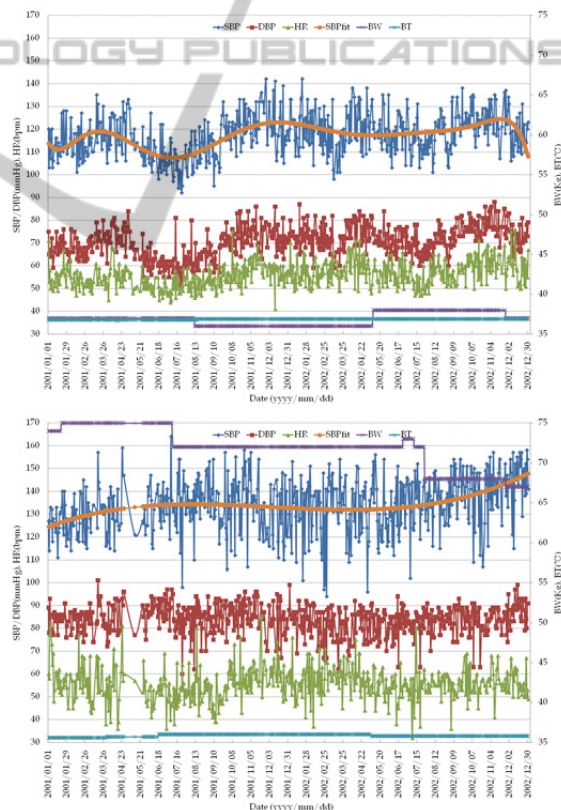


Figure 2: Profiles of daily HR, SBP, DBP, BT and BW in two years collected from a couple ([upper] wife and [lower] husband). Sporadic blanks indicate no measurement on those days. The brown lines are the polynomial approximation of SBP (9th order for the wife and 3rd order for the husband). Most data were measured in the afternoon of a day.

biorhythmicity differs in period and MESOR, amplitude and phase, zenith and nadir. Therefore, proper analysis and visualization of these data are indispensable in connecting daily physiological data to biorhythmicity and health condition.

2.2 Pre-processing of SBP

This paper uses only the daily SBP data from the above measurement in data analysis. Raw SBP data are often contaminated by spike-like noise and other artefacts due to poor contact and motion. The former is suppressed by a median filter and the latter is mitigated by a Savitzky–Golay filter.

2.2.1 Suppression of Spike-like Noise

Occasional spike-like SBP data are considered outliers and suppressed in the first step.

A median filter is a nonlinear digital filtering technique, usually used in the image processing field to remove speckle noise, or salt/pepper noise from images. The idea is to represent the signal by replacing an extremely large value with a reasonable candidate value. This is realized using a window consisting of an odd number of data. The values within the window are sorted in numerical order, and the median value, the sample in the centre of the window, is selected as the output of the filter.

When the window is moved along the signal, the output of the median filter $y(i)$ at a moment i is calculated as the median value of the input values $x(i)$ corresponding to the moments adjacent to i ranging from $-L/2$ to $L/2$.

$$y(i) = \text{median} \left(\begin{matrix} x(i-L/2), x(i-L/2+1), \dots, x(i), \dots \\ x(i+L/2-1), x(i+L/2) \end{matrix} \right), \quad (1)$$

where L is the length of the window.

2.2.2 Smoothing of Monthly SBP Profile

The Savitzky–Golay filter is used to smooth the data outputted from the median filter. The Savitzky–Golay filter segments the data as frames using a moving window, and approximates the data frames one by one using a high-order polynomial, typically quadratic or quartic (Savitzky & Golay, 1964).

For each input point $y(i)$, a digital filter output $z(i)$ can be expressed by a linear combination of the nearby input points as

$$z(i) = \sum_{k=-n_L}^{n_R} c_k y(i+k) \quad (2)$$

where n_L is the number of points on the left-hand side of the data point i , and n_R is the number of points on the right-hand side of i .

The Savitzky–Golay filter is to find a proper polynomial to fit all n_L+n_R+1 points within each window frame on the least-squares meaning, and to produce a filter output $z(i)$ as the value of that polynomial at position i .

To derive filter coefficients, c_k , we consider fitting a polynomial of degree M in i , namely $a_0+a_1i+a_2i^2+\dots+a_Mi^M$ to the values y_{-n_L}, \dots, y_{n_R} . Then, $z(i)$ will be the value of that polynomial at $i=0$, namely a_0 . The design matrix for this problem is

$$A_{ij} = i^j, \quad (3)$$

$$i = -n_L, \dots, 0, \dots, n_R, \quad j = 0, \dots, M,$$

The normal equations for the polynomial coefficients vector, $\mathbf{a}=[a_0, a_1, a_2, \dots, a_M]'$, in terms of the input data vector, $\mathbf{y}=[y_{-n_L}, \dots, y_{n_R}]'$, can be written in a matrix notation as below:

$$\mathbf{A} \cdot \mathbf{a} = \mathbf{y}, \quad (4)$$

The polynomial coefficients vector, \mathbf{a} , becomes

$$\mathbf{a} = (\mathbf{A}^T \cdot \mathbf{A})^{-1} \cdot (\mathbf{A}^T \cdot \mathbf{y}), \quad (5)$$

We also have the specific forms

$$\{\mathbf{A}^T \cdot \mathbf{A}\}_j = \sum_{k=-n_L}^{n_R} A_{ki} A_{kj} = \sum_{k=-n_L}^{n_R} k^{i+j} \quad (6)$$

and

$$\{\mathbf{A}^T \cdot \mathbf{y}\}_j = \sum_{k=-n_L}^{n_R} A_{kj} y_k = \sum_{k=-n_L}^{n_R} k^j y_k \quad (7)$$

Since the filter coefficient, c_k , is the component a_0 when y is replaced by the unit vector \mathbf{e}_k , we have

$$c_k = \left\{ (\mathbf{A}^T \cdot \mathbf{A})^{-1} \cdot (\mathbf{A}^T \cdot \mathbf{e}_k) \right\}_0$$

$$= \sum_{m=0}^M \left\{ (\mathbf{A}^T \cdot \mathbf{A})^{-1} \right\}_{0m} k^m, \quad (8)$$

where $-n_L \leq k < n_R$.

When the filter coefficient vector $\mathbf{c}=[c_{-n_L}, \dots, c_{n_R}]$ is obtained using Equation (8), the data can be smoothed using Equation (2).

2.3 Detection of Biorhythmic Change

Biorhythmic change is detected by the dynamic time warping (DTW) algorithm (Salvador and Chan, 2007). DTW is an algorithm used to measure the

similarity between two data sequences that may generally vary in temporal span and rhythmic tempo.

2.3.1 DTW Algorithm

The aim of DTW is to find the optimal alignment between two given data sequences under given criteria. The length of two sequences may differ and varies. The reference sequence $R=\{r_1, \dots, r_M\}$ with length M , and the test sequence $T=\{t_1, \dots, t_N\}$ with length N , are shown in Figure 3. The value of each black dot d_{ij} indicates the difference (distance) between the reference sequence r_i and the test sequence t_j , as described by Equation (9).

$$d_{ij} = \sqrt{(i - j)^2 + (r_i - t_j)^2}, \quad \begin{matrix} i=1, 2, \dots, M; \\ j=1, 2, \dots, N, \end{matrix} \quad (9)$$

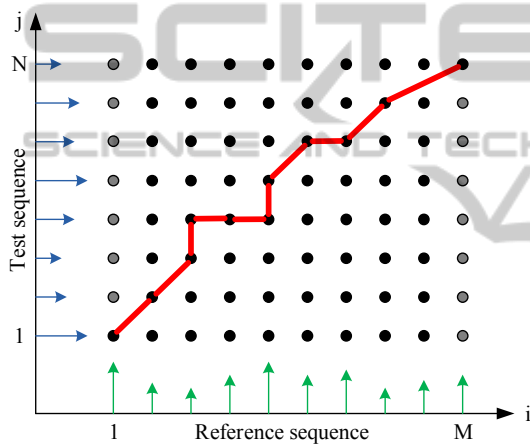


Figure 3: Dynamic time warping algorithm showing the optimal path (red line) between the reference sequence and the test sequence.

Thus, a two-dimensional $N \times M$ distance matrix, $D_{N \times M}$, is constructed where the element d_{ij} is the distance between the i^{th} data in the reference sequence and the j^{th} data in the test sequence.

As a similarity measure, the shortest path from the start (the lower left-hand corner of the distance matrix) to the end (the upper right-hand corner of the distance matrix) of the data sequence must exist among multiple possible paths.

The shortest path is determined using the forward dynamic programming approach with a monotonicity constraint.

$$P_{ij} = \min_{k \geq j} \{d_{jk} + P_{i+1,k}\} \quad (10)$$

where P_{ij} denotes the distance from the i^{th} and the j^{th} data node to the terminating node.

The overall minimum distance, $D(T, R)$, used as the similarity measure for two sequences (a smaller

distance value indicates a higher similarity) is determined from

$$D(T, R) = P_{11}, \quad (11)$$

2.3.2 Personal Reference Profile

A personal reference profile is created by averaging individual 24 monthly SBP profiles and used as the reference sequence in DTW calculation. Because the number of days in a month differs from month to month, and data loss unavoidably happens in daily measurement, the length of the reference profile is normalized to 30 days by resampling the daily measured raw data.

Two personal reference profiles for the wife and the husband are shown in Figure 4.

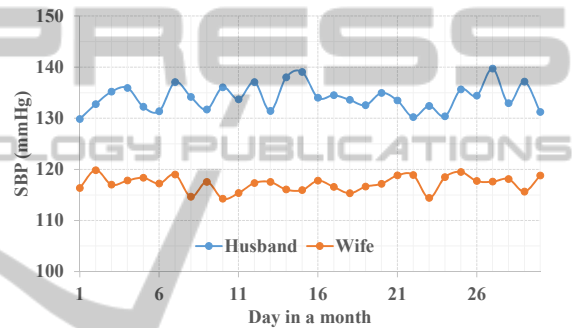


Figure 4: Personal reference profiles derived by averaging 24 monthly profiles of individual SBP data.

2.3.3 Biorhythmic Change Index

The personal reference profile is used as a reference sequence to calculate the overall distance D from monthly SBP profile using the DTW algorithm as shown in Equation (11). The D value is considered as a similarity measure describing the discrepancy between personal reference profile and monthly SBP profile, and serves as a biorhythmic change index (BCI) reflecting the monthly biorhythmic change. The smaller the value of BCI is, the more regular in biorhythmicity and the less change in health condition.

3 RESULTS

The monthly change of BCI, or the overall distance between personal reference profile and individual monthly SBP profile in two years is shown in Figure 5. The upper plot presents the outcome of the wife, the lower plot is for the husband. The BCI value was calculated by the DTW algorithm using the personal

reference profile as a reference sequence and the monthly SBP profile as a test sequence. The smaller the value of the BCI is, the higher the similarity has between the personal reference and monthly profile.

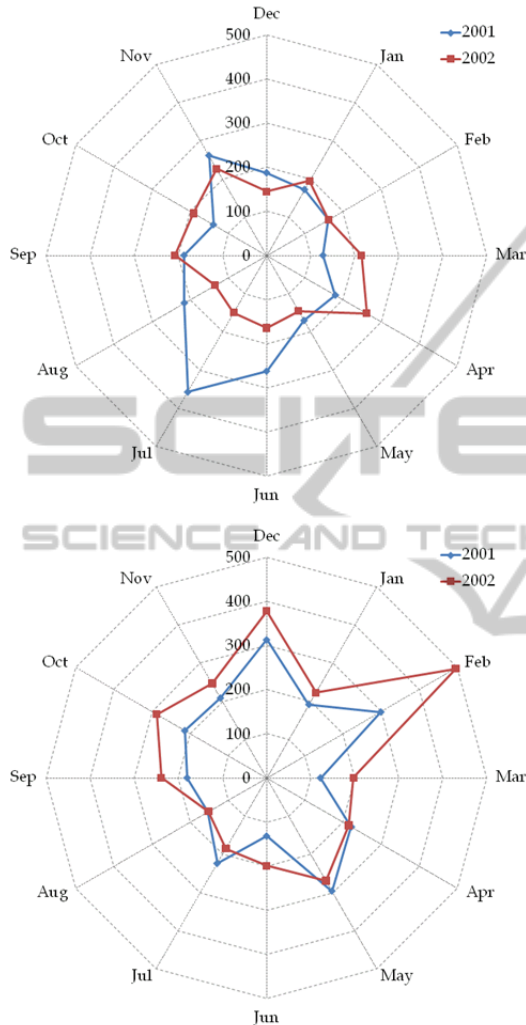


Figure 5: Monthly change of the BIC, or the overall distance between personal reference profile and monthly SBP profile in the wife (upper plot) and the husband (lower plot) in two years.

It is obvious that the monthly rhythmic change can be found in both the wife and the husband. Nevertheless, the exceptional change in the wife happened in July, 2001 (blue trace in upper plot), and husband in February, 2002 (red trace in lower plot). The onset of the symptoms usually insinuates certain alterations in physical or mental conditions. This implies that remarkable change in the health condition of the wife and the husband probably occurred in the respective timing point.

The above analytical outcome were confirmed to

be accordant with the couple's real situation by referring to their personal medical records, both were in poor health condition and were accepting treatment in the corresponding period.

In comparison with the noteworthy biorhythmic variations in July, 2001 of the wife and in February, 2002 of the husband, indistinctive change in other corresponding months in two years exhibits a monthly repetitive pattern of biorhythmicity in good health condition.

4 DISCUSSION

Many chronic diseases, such as diabetes, hypertension, arteriosclerosis, malignant neoplasm, cerebral and cardiovascular conditions, are silent killers that require a long-term course in disease development and threaten human beings in a latent way. Occasional or regular yearly health check-up are difficult to identify the onset of the symptoms and incidence of diseases at their early stage. Various home-based devices provide convenient approaches for daily measurement of variety of physiological data in daily life environment. Nevertheless, a huge volume of data accumulated over a long-term period usually contain abundant functional information but require proper approach in order to assess the significant signature in different physiological and pathological conditions.

As is well known, physical and mental conditions are affected by various endogenous and exogenous factors. They may include emotional, psychological, behavioural aspects, and as well the meteorological, environmental, geographical, and temporal factors. Therefore, it is difficult to identify the underlying regulatory mechanism which is responsible for various benign and malignant stimulants.

Instead of scrutinizing every detail of daily measurement of SBP, we applied an efficient DTW algorithm for tracking of biorhythmic alteration to reflect the health condition change. The results also suggest that it is possible to track not only physiological condition change in monthly base but also various specific events in daily base such as heavy intake of alcohol, mental depression, and other unusual incidents in daily life, provided the vast amount of physiological data is accumulated through daily measurement over a long-term period, and proper algorithm is applied to scoop out the valuable information.

Personal reference profile is currently obtained by simply averaging all of the monthly data. It is

apparent that the aging process affects the averaged personal reference profile, and evolution of the personal reference profile is desirable to adapt on monthly base gradually to reflect intrinsic biorhythmic change with aging process in the future study.

Although this paper presents only the outcome obtained from two elders in two years, it is promising to recognize the feasibility for tracking of monthly change in health condition by daily measurement of physiological data. More data from more persons in different age groups, longer period of measurement, and diversity of physiological and pathological conditions are preferable in further validation of the proposed method. More sensitive and more robust algorithms are also worth to be explored in depth on different temporal bases such as daily, weekly, monthly, seasonal and yearly.

5 CONCLUSIONS

In this paper, we applied the DTW algorithm to analyse the monthly rhythmicity using daily measurement of SBP from an elder couple in two years. Minor variation in monthly biorhythmicity indicates the physiological adaptation to internal and external factors temporally. The remarkable deviation out of usual physiological adaptation reflects the health condition alteration accordingly. It suggests that the recognisable unusual change provides an evidence to help making decision in daily health management and an insight into chronic disease control, and perception to deal with daily health problem more smartly.

The results also suggest that even it is difficult to identify any significant variation from the daily or the monthly SBP profile directly, proper analysis of the raw SBP measured over a long-term period is able to help tracking functional information of health condition change and serving as an effective evidence for health management.

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