Development of an Automatic System for Persistent Collection of Physiological Information

Toward Long-term Application in Biorhythm Monitoring and Healthcare

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Abstract: This study aims to develop an automatic system for persistent collection of physiological information such as pulse rate and SpO_2 in daily environment. The system includes a home-based user terminal and an Internet database server. The user terminal consists of a SpO_2 sensor and a bedside box. The bedside box receives the physiological data from the sensor by Bluetooth connection and relays the data to an Internet-based database server. This system was used to collect the data during daily sleep from a female volunteer at her thirties for a period of more than 15 months. Superior persistence characteristic in daily data collection was confirmed and achieved up to 93.1% of data collection rate comparing with many allied devices or systems that usually ranged about 25% or even less. Average length of menstrual cycles in the female subject was estimated 24.9 days by the cosinor analysis method using the collected data. The result showed satisfactorily accurate with comparing self-recorded length of 27.5±1.3 days. This system is expected to serve as a significant approach for long-term data collection and to obtain more reliable results for the purpose of tracking biorhythm and health condition change.

1 INTRODUCTION

Persistence characteristic in data collection is of fatal importance in daily healthcare application because tracking of biorhythmic change and health condition change requires reliable data accumulation over a long-term period. Inconvenient ways used in daily environment often disturb daily activities and lead to a lower rate in data collection which links to unreliable outcomes in deep mining of physiological data. This issue is usually treated by two ways: one is to generate surrogate data by missing data analysis, and another is to increase data collection rate by usability improved approaches.

Missing data can be estimated by diversified surrogate methods such as linear or cubic interpolation, bootstrapping, maximum likelihood, multiple imputation and other statistics-based methods. However, surrogate data commonly differs from the real measured data in many aspects such as intrinsic data features and statistical behaviours. A series of studies aimed at investigating these effects on HRV in temporal and frequency domains as well as nonlinear aspect had been conducted using different methods (Kim et al., 2007, 2009, 2011).

On the other hand, diversified modalities for conveniently monitoring various physiological data were explored in the past decades. ECG or pulse can be recorded not only on a bed during sleep (Ishijima, 1993; Watanabe et al., 2003; Chen et al., 2005; Lim et al., 2007), but also on a chair during sitting (Lim et al., 2006), and even in a bathtub during bathing (Tamura et al., 1997, 1998).

This study serves two purposes. The first is to develop an automatic Internet-based system suitable for persistent collection of multiple physiological information in daily life environment over long-term period without much discomfort to the user. The second is to assess physiological interpretation of such long-term data through various mathematical means. This paper will demonstrate the outcome in estimating biorhythmic change such as a female's menstrual cycle by applying the cosinor analysis method to these data. Finally, we will discuss its potential application in long-term biorhythm monitoring and health condition tracking for daily health management.

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2 METHOD

This system includes two parts: a user terminal and an Internet-based database server.

Outline of the system is showed in Figure 1. The user terminal consists of a SpO_2 sensor and a bedside box for physiological measurement at home. The database server at remote serves for data storage and further data analysis.

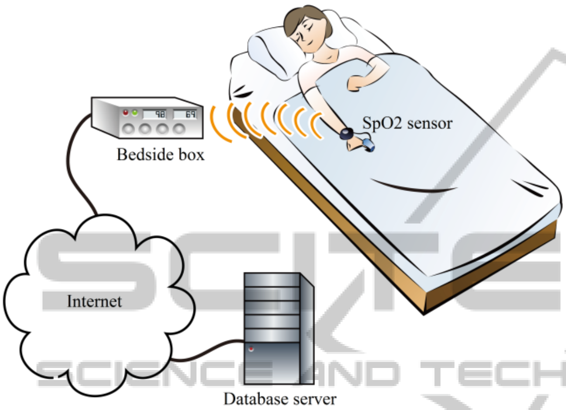

Figure 1: Schematic of pulse rate and SpO_2 data collection during sleep. By attaching a Bluetooth-enabled SpO_2 sensor to a fingertip, the nearby bedside box establishes a Bluetooth connection with the sensor automatically, and receives the data from the sensor continuously. These data are transmitted to a database server via Internet connection.

When the user goes to bed and inserts a finger into the sensor device, the device will be initiated automatically and connected to a Bluetooth module inside the bedside box.

The physiological data such as pulse rate and SpO_2 is measured and transmitted to the bedside box by Bluetooth connection. The bedside box will receive and unpack the data packet sent by the sensor device, extract useful information and repack these data in a packet, and send one packet to the remote database server every minute via the Internet connection.

The server unpacks the received data and stores the data in the database. The daily accumulated data will be analysed and its outcomes will be visualized on webpage.

2.1 User Terminal

There are two separate parts in a user terminal. A Bluetooth-enabled wristwatch type pulse oximeter (Model 4100, Nonin Medical, Inc., USA) is used as a sensor device. A bedside box consists of two main modules: AKI-H8/3069F LAN board (Akizuki Inc., Japan) and Parani ESD 200 Bluetooth module (SENA Technologies Inc., Japan).

The AKI-H8 board contains a RTL8019AS full-duplex Ethernet controller and a LAN port, which allows TCP/IP protocol stacks to be used.

Parani-ESD 200 is a module for short range wireless communication using Bluetooth technology. It can communicate with other Bluetooth devices that support the Serial Port Profile (SPP). This module is registered to the sensor device and will create a connection automatically when the sensor device is turned on.

Data received from the sensor device will be transmitted to the H8/3069F board through RS-232 interface. After the connection between ESD 200 and the sensor device is established, the data transfer is ready. The application starts to read each byte from the RS-232 buffer. If this byte turns out to be 1, then read the next byte and determine whether it is the first frame. When the first frame is found, the application will receive the rest of the packet and decode the pulse rate, SpO_2, signal status and battery status.

After one packet is received in the ring buffer, data such as pulse rate, SpO_2, signal status and battery status can be decoded. The detailed flowchart of decoding data from the sensor device is showed in Figure 2.

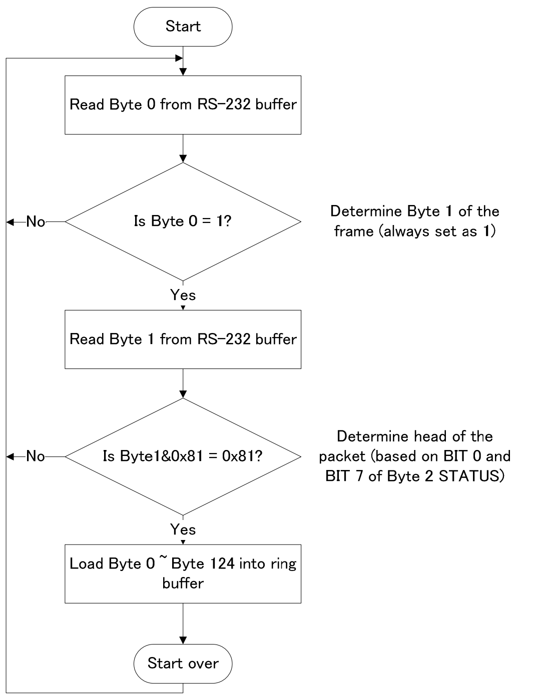

Figure 2: Procedure for decoding data stream from the sensor device.

When the power of the sensor device is turned on automatically due to a fingertip insertion, it will attempt to connect a registered host Bluetooth device. Once the connection with a paired bedside box is successfully established, the sensor device will start sending data packets including pulse rate, SpO_2 and status data such as signal quality and battery status.

Range of data transmission is roughly 10 meters which is enough for a daily sleep environment in a bedroom. The radio frequency band is 2.4 GHz. The Bluetooth profile for data transmission between the bedside box and the sensor device is the Serial Port Profile (SPP).

The sensor device transmits data to the bedside box by a packet format consisting of 25 frames. Each frame consists of 5 bytes. Three packets, or totally 75 frames, are transmitted every second.

The bedside box has two major functions as follows.

1. Connect to the Bluetooth-enabled sensor device wirelessly, and receive, unpack and reorganize the data transmitted from the sensor device.
2. Send the reorganized data packets to the database server once a minute.

There are totally 264 bytes as two sections, a head section and a data section, in a reorganized data packet. The head section consists of the first 24 bytes and contains auxiliary information such as software version, bedside box ID, sensor device ID and some reserved bytes. The bedside box ID is bonded with user information, so that the uploaded data can be saved and retrieved using a user ID.

The data section includes information such as pulse rate, SpO_2, battery status and signal quality in the previous minute, and has totally 240 bytes.

The bedside box receives three packets from the sensor device every second. Since the data transmission rate is fixed, the application will pick up the first packet among these three packets, decode the packet and repack the necessary data into the data section with combining the head section in order to reorganize an upload packet.

Once sixty upload packets are fulfilled, the bedside box will send the upload packet including the head section and the data section up to the database server every minute.

If the sensor device is turned off when the user's finger leaves the sensor, data transfer will stop. However, the data already in the upload packet buffer still exist. Once the data transfer resumes, those unsent data will be uploaded to the database server at the wrong time stamp. The application will prevent this mistake by adding a 1-second timer.

When the receiving procedure starts in the bedside box, a 1-second timer will be started. After any packet is received, the application will check and clear the 1-second timer. If the timer has already ran out, which means that the application hasn't receive any packet in 1 second, the application would clear the whole upload buffer to avoid data uploaded at the wrong time stamp.

Because there is no built-in clock on the AKI-H8/3069F board, time information for every packet uploaded to the database server will be added on the server side. Because the packet size is small, the delay due to data transmission on the Internet is less than 10ms and ignored.

The detailed flowchart of uploading data packets to the database server is showed in Figure 3.

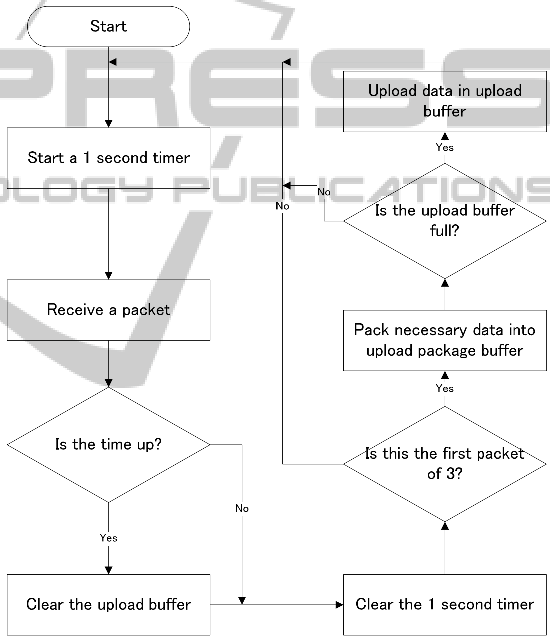

Figure 3: Procedure for uploading data from the bedside box to the database server.

2.2 Database Server

The database server can receive the data packets sent from the bedside box, extract relevant information from the packets, store the data into the database and provide the accumulated raw data to an application server for advanced functions such as data analysis and visualization. The database was implemented by using an open source MySQL.

A data reception application was developed on the Apache Tomcat platform which is an open source software implementation of the Java Servlet and Java Server Pages technologies. The data reception application keeps listening to the prescript socket port. Once a packet coming from the bedside box arrives, the data reception application will acquire and unpack the packet with the protocol described above. The decoded data will be saved into the database.

2.3 Data Collection

Physiological data collected during sleep by the user terminal include pulse rate and SpO_2, as illustrated in Figure 1. When the subject goes to bed, wears the wrist-type sensor device and inserts a fingertip into the sensor probe, the sensor device will be triggered off and start searching the nearby bedside box which is in a stand-by state waiting for the connection request signal from the sensor device. The Bluetooth wireless connection between the bedside box and the sensor device is established automatically. Pulse rate and SpO_2 data are collected from the sensor device via the Bluetooth connection and are transmitted continuously to the database server by the bedside box during sleep automatically. When the subject gets up and removes the sensor probe in the morning, the Bluetooth connection is closed, the bedside box goes into stand-by mode again, and the data collection procedure is terminated.

After an informed consent was obtained from a female volunteer at her thirties of age, we collected daily physiological data from the subject during her daily sleep. The female volunteer collected data for 442 days over a period of 475 days across 2007/12/13 to 2009/3/31. Data collection rate is 93.1%. Comparing with many allied devices or systems which is usually about 25% or even less, data collection rate by this system is fairly high due to its convenient usage and full automation in daily utilization.

2.4 Data Processing

To demonstrate the performance in estimating female's menstrual cycles using such kind of data accumulated over a long-term period, the following three steps are applied.

The daily pulse rate mode value is calculated in the first step from the noise-suppressed pulse rate data which has about 20,000 data points during a 6-7-hour sleep episode.

The second step has two tasks: (1) to smooth the daily mode value profile using a Savitzky–Golay filter, and (2) to remove a slower baseline wandering (which may imply seasonal biorhythmic change and remain to be studied in further deep data mining in the future) using a multi-rate filter.

The rhythmicity is estimated in the third step from the detrended profile of the daily mode value using the cosinor analysis method.

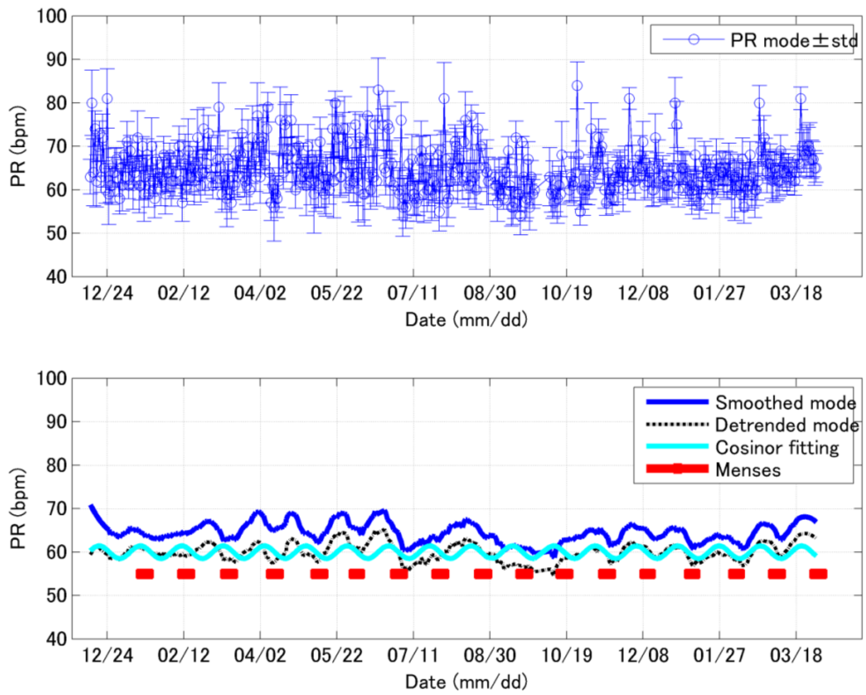

Figure 4: Upper subplot: PR mode value and standard deviation profile; Lower subplot: menstrual cycle estimation procedure. Red horizontal bars denote the menses periods that were recorded by the subject.

3 RESULTS

The cosinor analysis method is often used to estimate biorhythms with regular cycle length from biological time series data (Nelson et al., 1979). We determine the optimal parameter set (M, A, ω, φ) to approximate the detrended mode data using a cosine function $f(t_i)$, as showed in the equation (1), by minimizing the residual sum of squared (RSS) errors between the detrended mode data and the corresponding value generated by the function $f(t_i)$.

$$f(t_i) = M + A\cos(\omega t_i + \varphi) \quad (1)$$

where t_i represents the time of measurement of the i^{th} data, M is the mean level (MESOR) of the cosine curve, A is the amplitude of the function, ω is the angular frequency (reciprocal of the cycle length) of the curve, and φ is the acrophase (horizontal shift) of the curve.

The optimal length of the average menstrual cycle is estimated 24.9 days. This compares with the average self-recorded menstrual cycle length of 27.5±1.3 days which is derived from total 16 cycles ranging from 25 to 30 days during the data collection period. The estimated length has an error about 9.5%.

The estimation procedure and its outcomes with overlapped self-record are showed in Figure 4. The upper subplot shows daily mode value and its standard deviation profiles, the markers “o” and vertical bars “|”, terminated at the upper and lower ends by short horizontal lines “-”, show the mode values and standard deviation of the pulse rate data in daily sleep episodes. The lower subplot demonstrates the menstrual cycle estimation procedure, the bold blue line shows the smoothed profile of the daily mode values, and the black dotted line shows the detrended result of the smoothed mode profile. The cyan line is the cosinor-fitting result to the black dotted line. Red horizontal bars denote the menses periods that were recorded by the subject.

Data are plotted on the day-by-day basis along the x-axis. The y-axis denotes pulse rate in the unit of beat per minute (bpm). Some sporadic discontinuities can be seen, as no data were collected during those days.

4 DISCUSSION

Purposes of this study aim mainly at developing a user-friendly and convenient system available for daily physiological information collection over long-term period, and providing more reliable data for further analysis.

Data collection rate can be used as one of the indicators for evaluating the usability of the system. It seems promising to achieve fairly high rate in data collection over 15 months. We examined the reliability of these data by applying the cosinor analysis method to estimate the menstrual cycle, and achieved reasonable accuracy with estimation error smaller than 10%.

Although the cosinor analysis method does not require that the data be sampled at equal intervals, and it also tolerates incidents of missing data, it provides an accessible means of estimating the periodic signature in physiological data. However, the cosinor analysis method postulates that the data should be reasonably represented in a deterministic cyclic form with a constant period. This prerequisite is not always suitable in female menstrual cycles. To deal with irregular cycle cases and explore other intrinsic biorhythms, more data mining methods will be conducted to extract various features in time domain, frequency domain and chaotic domain in the future.

Further interpretation for the physiological significance such as health condition change and biorhythmic fluctuation from these long-term data will be one of the most important tasks in the coming data analysis. Deep data mining on different temporal scales, such as daily, weekly, monthly, seasonal and even yearly, will be conducted to reveal the statistical links among health condition change and various data signatures over a long-term period.

5 CONCLUSIONS

The system was examined by a female volunteer in more than 15 months and confirmed its friendly usability, performance and reliability in systematic aspects such as data collection and data analysis. Higher rate in data collection over a long-term period, and more reliable outcome from the long-term data were confirmed and achieved. This study is expected to be served as a part of SHIP (Scalable Healthcare Integrated Platform) project (Chen et al., 2008).

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