On-site measurement, data process and wavelet analysis techniques for recognizing daily physiological states

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1. Introduction

The human body autonomously controls its physiological states in order to protect and sustain its life. Recently, it has become possible to track daily cyclical characteristics of the physiological states and understand its system and effects (Haro & Panda, 2006). In order to observe the daily physiological changes in normal life, the ability to acquire long-term stable measurements is crucial, but without interfering with daily life activities. Also, in real life situations where there are a variety of interruptions and extraneous noise sources, data must be extracted and processed with a high degree of fidelity to be meaningful. The challenges are to develop wearable measurement instrumentation and data analysis techniques to extract daily changes in physiological state. Recent advancements in semiconductor technology allow for small and light-weight sensors to be attached to the body without any interference to daily function. Commercially available mobile devices, such as cell phones, are advanced enough to provide on-site computational power and data storage. Body temperature and heart rate are the two chosen attributes for measurement since both exhibit daily changes for clinical measurements (Burger et al, 1999), (Simpson & Galbraith, 1905), (Sandra & Hanneman, 2001). On the other hand, the study of cyclical physiological mechanisms, such as biological clock (Mendlewicz & van Praag, 1983) becomes applicable only when being monitored over periods of time. Noise elimination, range filtering and techniques to recover damaged data are utilized to handle the existence of several types of noise, interference and other constraints of daily life. For data analysis, observed physiological state change is subtle and may not be represented by a series of sinusoidal oscillations. Traditional frequency decomposition techniques such as Fast Fourier Transform (FFT) or low pass filtering can cause data to be misinterpreted. Therefore, a wavelet approach is applied to handle this issue since it is a time and frequency shift algorithm that conforms its wave form into observed changes. Test results are presented, which clearly exhibits the daily changes. A wearable device, stable measurement techniques and responsible analysis make it possible to continuously monitor and hear the whispers of our body's physiological states essential for human life.

2. Physiological Data Collection

Physiological states are induced and controlled by the activities of the sympathetic and parasympathetic nervous systems. These nerves work autonomously, rarely drawing attention to their presence. However, they are certainly exhibiting changes in heart rate, body temperature or other characteristics with subtle signals, detectable with clinical measurements. The primary purpose of this investigation is to ascertain the physiological attributes in daily life by using long-term on-site monitoring methodology and meaningful data extraction techniques.

To monitor normal physiological states of the human body, and especially the daily cyclical changes, it is necessary to use a compact, lightweight and wearable mobile device.

It also requires data processing and storage functionality associated with data acquisition in order to ensure continuous monitoring that can adapt to a wide range of life situations and environments.

Cellular phones fit this bill perfectly since they have become a convenient fixture in daily life, carried by a majority of the population at all times.

Additionally, noninvasive measurement techniques are required when being applied to subjects so as not to create discomfort or distractions. With current technologies, these techniques include measuring heart rate, body temperature, brainwave activity, galvanic skin response, and the like. Body temperature and heart rate are two good candidates to be measured since both exhibit measurable changes daily (Burger et al., 1999), (Simpson & Galbraith, 1905).

Recent advancement of semiconductor technologies realizes highly accurate, small and light-weight sensors. However, even when using such advanced sensors, there are considerable constraints for achieving stable and accurate readings when they are applied to the human body exposed to multiple factors encountered in daily life. Moreover, while compact and lightweight instrumentation is important, the capability to perform measurements on an extended basis is imperative for achieving the measurement objectives.

Suppose that time historical data contains subtle signals which exhibit certain physiological state characteristics, even though masked by noise. For body temperature, the following description can be referenced from available literature (Sandra & Hanneman, 2001). "In humans, a diurnal variation has been observed lowest at 11 p.m. to 3 a.m. and peaking at 10 a.m. to 6 p.m., which are dependent on the periods of rest and activity." In general, about 1 degree Celsius deviation is considered normal diurnal change. Heart rate is another example, where circadian change is observed with dozens of heart rate fluctuations per minute between day and night.

On the other hand, the study of cyclical physiological mechanisms, such as a biological clock, becomes applicable and meaningful only when monitored over long duration of normal life.

Since data measurements need to be gathered under normal living conditions, this approach is not immune from providing erroneous data interpretation, especially when data have been corrupted due to sensor detachment or contamination from ambient noise. Body temperature and heart rate can also be affected by factors such as physical activity and other situations. Activities which require the removal of clothes or removal of sensors, such as bathing or changing clothes, may temporarily disrupt the ability to capture the data in measurements. Therefore, measured data may not be a complete series of day-long profiles to show circadian changes first hand (Philippa et al., 1986).

The assumption is that even after experiencing a number of fluctuations and interruptions induced by a variety of reasons, the overall profile of diurnal change can be distilled through robust measurement techniques, data processing and analytical methods. Therefore, an analysis which can evaluate data incompleteness and quality must also be incorporated. Next, data processing techniques that can segregate corrupt portions of data and recover meaningful measurements, in conjunction with noise filtering, should be employed to alleviate negative influence on data before executing the diurnal analysis.
The measurement and compensation techniques for degraded data are discussed in the following sections.

3. Instrumentation and Measurement

One of the project objectives is to determine whether ubiquitous devices can perform the role of detecting valuable biorhythmic information without causing undue discomfort to the user.
By collecting data on a continuous basis, it is difficult not to encounter anomalies in instrument readings due to system noise, environmental interference, physical constraints, or the need to interrupt the measurement process for unforeseeable reasons. Therefore, in addition to requiring a high-degree of measurement resilience associated with accurate sensors, adequate pre-data processing techniques are expected without deteriorating the measured data before proceeding to extract physiological parameters.
We examine below incidents and conditions that may cause degradation in data accuracy.

3.1 Anomalies

Because of the extended periods needed to extract physiological state measurements, the sensors themselves must not be invasive. Normally, sensors are attached to the skin, and they can provide erroneous data if detached for any reason. For heart monitors, this can be easily detected when sensor feedback returns a pulse of zero. It is more difficult to quickly determine whether a temperature sensor becomes detached, when data points show a surrounding temperature reading similar to that of the subject. The ambient temperature should be measured for providing reference information. When ambient temperature and expected body temperature ranges are known, the data can be segregated.
We can categorize two anomalous conditions for temperature measurement, 1) a loose fitting sensor and 2) a detached sensor. The first will cause data intermittency for an actual body temperature acquisition or show intermediate temperatures between body and ambient. It is difficult to detect this symptom and shall be dealt with as noise. If the denoising process works well, this erroneous data will be filtered out. The detail is discussed in the wavelet analysis section. Meanwhile, the sensor loose fitting may yield a sensor detachment. The sensor detachment is detected by monitoring the temperatures including the surrounding during entire test period, which yields catastrophic measurement errors. This is handled through range filtering by detecting body temperature changes over extended periods with distinct characteristics.

3.2 Noise

Every electronic device emits system noise. In a Gaussian noise profile, a data averaging approach can provide adequate noise suppression. However, other sources of disturbance are convoluted in the data. The environment produces noise that degrades data quality. For a heart rate sensor, activities of short duration which induce changes, such as walking up stairs, or stress propagated by individual incidents, is categorized as noise for our purpose since such a fast heartbeat does not indicate a normal physiological state. Rather than simply applying an averaging process, we examined the data using wavelet decomposition associated with a denoising technique to filter out such data fluctuations.

For temperature sensors, in addition to physical activities, ambient temperatures may be erroneously captured instead of body temperature. Therefore, it is also crucial to examine the noise characteristics of the data for recognizing the state of the measurement.

3.3 Physical Constraint

There are times, such as for battery replacement or recharging, when data collection needs to be temporarily interrupted. Problems attributed to the system, and intentional but temporary system terminations are also realistic conditions when measuring for long durations. An analytical data recovery procedure for missing data becomes essential. This process is also necessary since the placement of even small sensors can interfere with showering and other daily activities, and may require sensors to be detached from the skin. Discontinuities in data series are inevitable when measuring for entire days, even without anomalies or heavy noise.

3.4 Measurement System Configuration

To minimize concerns, we have chosen the chest and inside upper arm areas for the heart rate and body temperature sensor locations, respectively. Data transmission to the mobile phone, located at the waist, is done with a reliable and proven wireless connection such as Bluetooth. Other less power robust wireless systems can be reasonable alternatives. The system configuration is shown in Fig. 1.

Communication capabilities of the cell phone are ideal for providing connectivity to the database to compute and interact with other systems. In our case, analysis was performed at a remote server. Depending on resources and computational ability of the mobile handset, on-site analysis may be an alternative option. Moreover, this convenient cell phone based configuration provided additional benefits such as system monitoring, notification messages, alarms and access control.

If an ambient temperature is that of the subject, it is more difficult to detect a sensor detachment or reading error of the actual body temperature. Therefore, an ancillary sensor is implemented to measure ambient temperature for providing reference information.

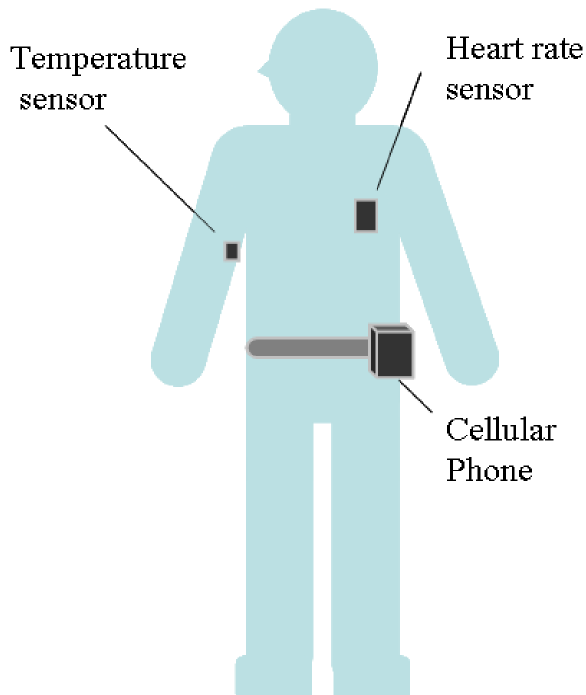

Fig. 1. Measurement System Configuration

4. Wavelet Analysis

Wavelet analysis is an excellent method for extracting signals caused by a change in state with arbitrary time and frequency.
In order to extract day-long physiological state change information, data decomposition and filtering is a straightforward approach. However, the observed changes of heart rate and body temperature are subtle and do not have any theoretical basis that can be represented by a series of sinusoidal oscillations. Therefore, traditional frequency decomposition techniques such as Fast Fourier Transform (FFT) or low pass filtering methods can cause data to be misinterpreted.
The applicability of wavelet analysis was examined in conjunction with related numerical data processing techniques.
Firstly, we focused on the noise suppression capability of the wavelet method. The term denoising refers to the process of extracting and eliminating overlaid noise from meaningful information (Misiti et.al., 2002). Several methods are proposed and available (Qi et.al., 2002), (Donoho & Johnstone, 1998), (Strang & Nguyen, 1996). To recognize noise characteristics in the measurement, the denoising of wavelet coefficients is applied in conjunction with decomposition to determine data validity.
The physiological data is normally benign and can be limited to within a certain range corresponding to known biological activity. Therefore, range filtering and data prediction techniques are applicable to the process. Data intentionally terminated or otherwise missing is recovered by using proximity data and cyclical characteristics to predict what is absent.
In wavelet analysis, the border extension technique was proposed to accommodate data points to the analysis. We note that existing border extension methods were referenced but are not adequate for this purpose (Rout & Bell, 2004). Rather than extending data to cover

missing ranges, we predict missing data based on data continuity. A boundary constraint recovery approach was proposed and tested since the corrupted areas are found mid-stream, and can be recovered by using boundary information preceding and subsequent data of the corrupted region.

After these elimination and recovery processes are applied to the raw data, wavelet data decomposition techniques are executed to extract steady physiological characteristics over periods of hours and days. Since the improvement heavily depends on data characteristics, we examined the optimal strategy for each data using different scaling factors and mother wavelet.

In order to apply wavelet analysis for detecting long-term pattern changes from the readings, as explained in the previous section, the followings concerns are addressed.

1) Recovery of missing or corrupted data caused by interruptions in the data gathering process to create necessary data points.

2) Appropriate handling of data noise acquired during the measuring process to provide statistically valid data representative.

3) Selection of a proper wavelet methodology depending on data characteristics, since the objective is not to find a specific waveform but to recognize a circadian profile of state change.

4.1 Data Recovery

As mentioned in the former section, if fluctuating data are detected and determined to be corrupt, those portions must be eliminated and recreated in order to perform a wavelet analysis on the entire range of data. Since wavelet decomposition generally requires a constant interval, missing data must be recreated for the sampling purpose. The border extension method was developed for this reason to avoid border distortion of finite length of data. However, this is not directly applicable to missing data found mid-stream which we handle here. If data is corrupted due to sensor detachment or other anomaly, these points must be eliminated and recreated with the remaining data to ensure the continuity required for wavelet analysis.

In this experiment, data points are in abundance, and show only minor changes throughout the day. Therefore, we can predict and recreate the missing data using the preceding and subsequent data of the affected area.

The boundary constraint recovery approach named in the former section, the proposed method, assumes that the preceding and subsequent regions of missing data have nearly identical information in terms of data continuity. From this theory, the algorithms of periodic prediction based on the Spline interpolation method are employed, as explained in Fig 2.

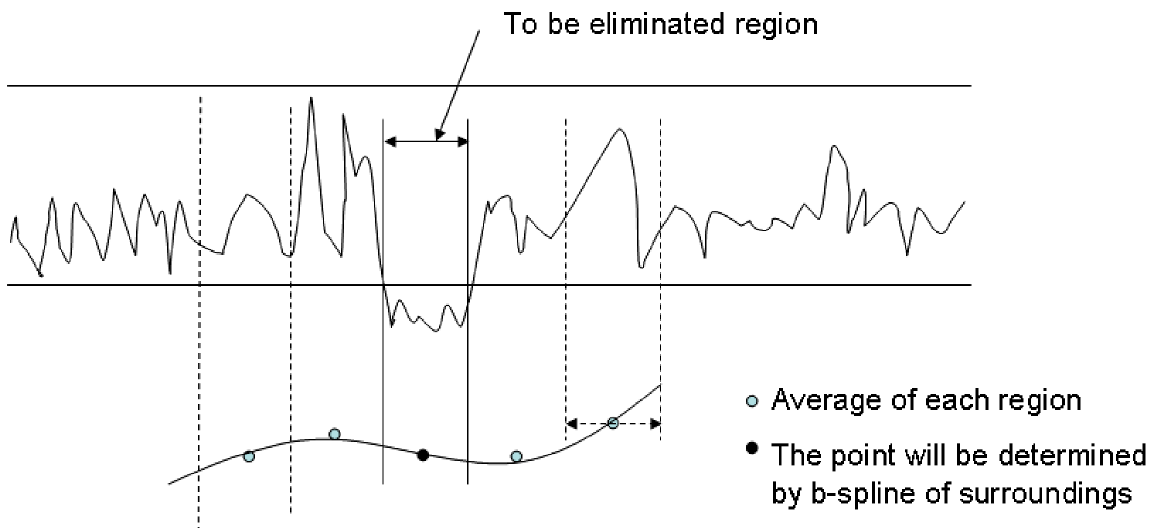

Fig. 2. Interpolation Technique for Corrupted Area

Beside anomaly or intentional detachment, corrupted data specific to heart rate includes changes in pace when placed under stress or during increased activity on a temporal or unexpected basis. For heart rate, short-range fluctuations during specific occasions have a continuous profile. Therefore, wavelet technique is also applicable to detect this region at the data filtering pre-process.
On the other hand, body temperature measurements are vulnerable to disruptions caused by sensor detachment or misreading from surrounding thermal sources.
Fluctuations beyond +/- 1 degree Celsius from the normal temperature can be eliminated as anomalous events or erroneous data theoretically as mentioned in the section 2. Such narrow band range filtering technique is applied and tested for body temperature.
Other divergent data, such as zeroes and overflows, if they are observed, must also be eliminated. Data must be recreated without deteriorating the signatures we wish to detect.

4.2 Noise filtering

Sensors are vulnerable to noise emanating from not only the environment but also the device itself. Unlike theoretically captured anomalous out-of-range data or instrument anomalies identified at the pre-process and recovery, noises are generally difficult to segregate. Wavelet denoising technique is applied at the pre-process to examine the baseline data. Since the denoising method is for shrinkage of the wavelet coefficients, this process is used for recognizing the noise characteristics of the measured data before detecting physiological state change. The purpose here is pre-process and noise assessment. The fixed hard threshold is applied here as a simple approach for the data evaluation. The detail and extended techniques are explained in the reference (Misiti, et al., 2002). Noise under electric fields generally has random distributions, which are handled using an averaging technique, but also through a wavelet denoising process that suppresses the non-dominant contribution to the wave form.
It should be noted that the pre-process provides three categories of information; the anomaly markers, the actual body condition driven by daily activities, and the noise distribution of the system in order to ensure a stable physiological state detection.

5. Measurement and Evaluations

For tracking heart rate, the sensor produces four data points per minute, which are then converted to beats per minute, of which 5760 are measured over a 24-hour period.
Once reconfigured through the aforementioned data evaluation and recovery process, it is subjected to the wavelet analysis with a proper level. The 12th power of two (2^{12} =4096) is the maximum resolution level for the 24 hours of measurements captured. The 13th order is 8192 about 34 hrs. Figure 3 illustrates a range of about 8200 data points. Since wavelet analysis is coordinated using binary systems, actual measurements may not precisely match the data extraction and specific data sampling intervals.

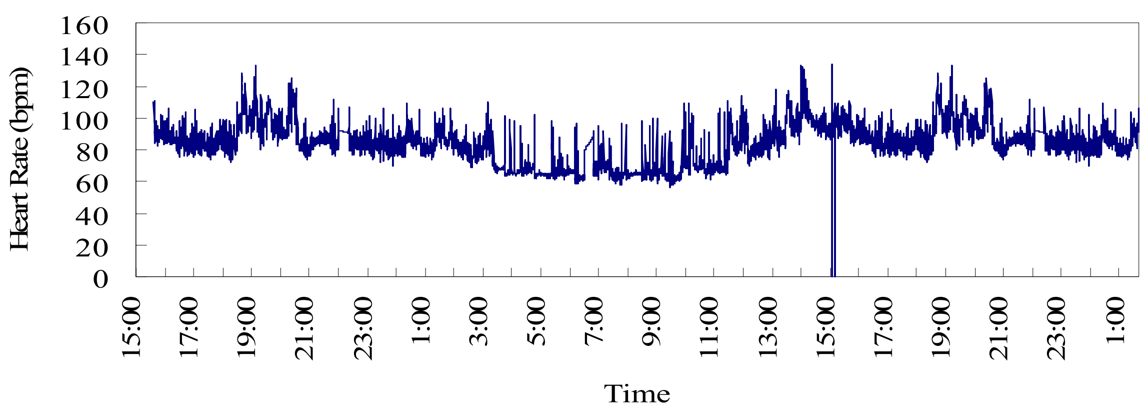

Fig. 3. Heart Rate Measured Raw Data

To accommodate the required number of data points from available data, the aforementioned border extension method can also be applied. However, this padded data can exaggerate the data characteristics since there is no theoretical validation that data have either periodic or symmetric or other specific profile at that region. It has the potential to conceal the state change and thus hinder our primary objective. Therefore, data prediction using time shift interpolation for the required interval was applied and compared with the extension methods. The method is similar to the data recovery of the eliminated portion, but the linear interpolation based on the continuity between the adjacent two points.
By assuming data characteristics, the border extension methods are executed, which can create data points to proceed directly to the wavelet analysis. We examined their effects as a comparison with the proposed interpolation technique. It is noted that for direct comparison, the decomposition for each analysis was the same as the decomposition level of 10. The comparisons with the extensions were provided in Fig. 4. In testing, a border was extended from 24hrs. to 34hrs. to create binary data points for wavelet analysis. In Fig. 4, the Periodic Boundary Extension means that the extended 10 hours was copied from the prior data between 14hrs. and 24hrs. to retain periodic characteristics of the data that yields a standard periodic extension. The Recursive Boundary Extension means that the extended data was created by copying the initial 10 hours of data into the period after 24hrs. that is assuming data repetition of a 24hr. cycle. Although they can also provide circadian profiles, the extended area beyond 24hrs. is less accurate and may lead to some misinterpretation. The 10 hour extension is rather large and may not be realistic for actual data adjustments, but it

should be noted that in any case, these techniques implicitly include the assumption that data must be periodic or diurnal. Therefore, we propose that data should be processed within 24 hrs. on a daily basis and adjusted to create binary data points by interpolation for wavelet analysis. For comparison, the proposed interpolation approach of the existing data was presented, which created the same number of data points within 24hrs. to fit a wavelet analysis. It showed better circadian characteristics.

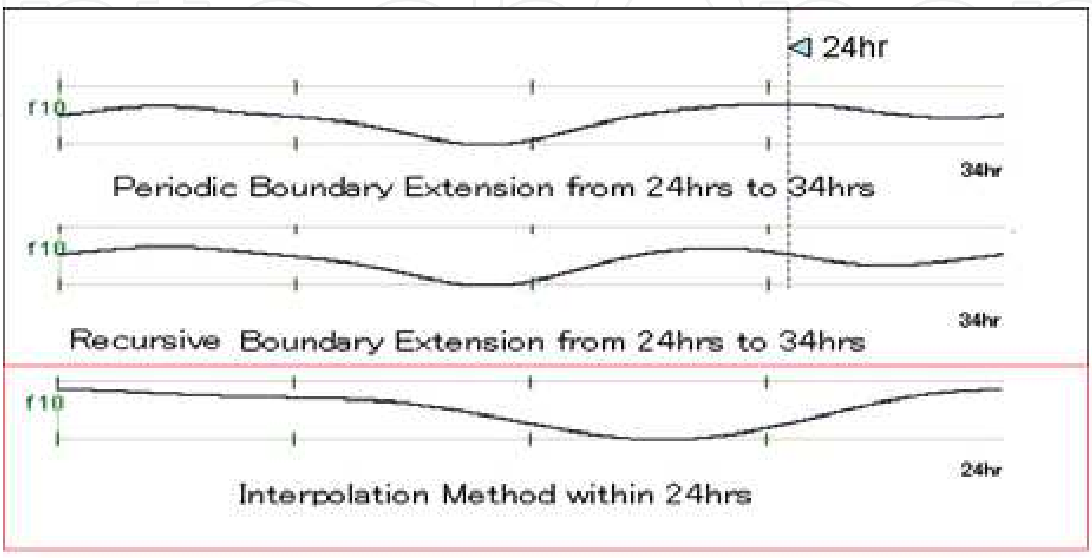

Fig. 4. Comparison with Boundary Extension Methods and Interpolation

For body temperature, the data were captured every second, and is presented in Fig.5. The data fluctuated due to much noise and interruptions. Realistically, body temperature does not need to be captured every few seconds. However, before proceeding to averaging, interpolating or wavelet denoising, the corrupted data is assessed and eliminated and recovered by the proposed process. Otherwise, the data contaminated due to sensor detachment or reading error will be convoluted into the analysis stage.
There was large corrupted period around from 21:00 to 0:00. This is suspected as a sensor detachment since it shows a temperature similar to the ambient one. The period after 12:00 was also corrupted since they showed beyond the range filtering criteria of the normal temperature, which is supposedly caused by a sensor loose fitting. The large noise shown between 18:00 and 19:00 is supposed to be an electric interference noise, since they are distributed around the average temperature. After coming back from the corrupted period from 21:00 to 0:00, the random noise level became slightly higher than the preceding period except for between 18:00 and 19:00. There may be a choice to execute a short time averaging to filter out these random noises. In this case, however, we didn't execute an averaging as a pre-process in order to examine the capability of the wavelet analysis. The range filtering criteria was set slightly wider to +/- 1.5 degrees Celsius to capture a sufficient number of data reflecting the data noise level.

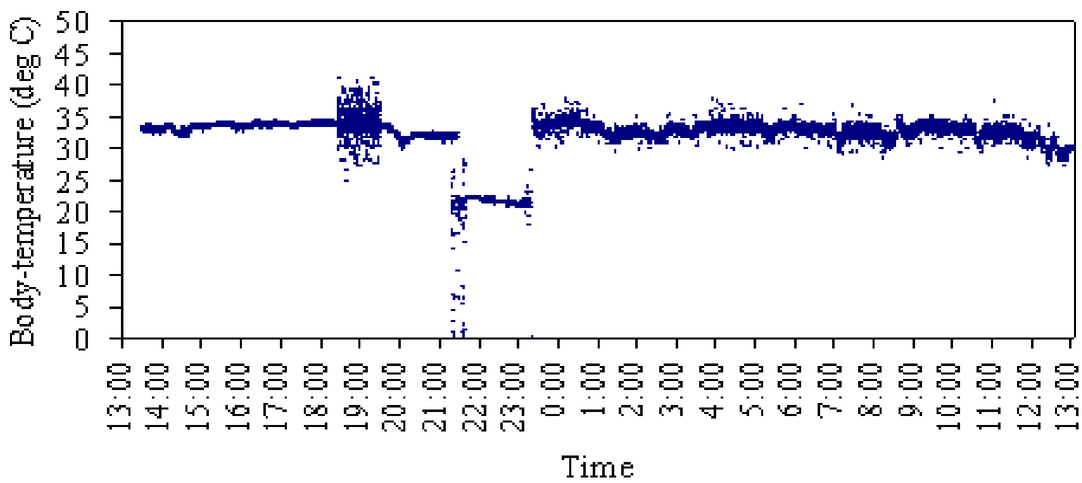

Fig. 5. Body Temperature Measured Raw Data

Figure 6 shows the result of the decomposition up to the level 10 for heart rate for the 24 hours of data. The decomposed residual profile represented by f10 in Fig.6 shows the diurnal change clearly. It should be noted that the profile has neither a 24hours cycle sinusoidal shape nor a state change having two separate stages. We collected almost similar data profiles over different days. The comparison of day to day changes and their physiological meanings are not addressed here, which must be conducted by accumulating a series of test data over several days and consulting with medical professionals. It is also difficult to reproduce a diurnal profile change, such as body clock shifts, artificially for simulation purpose. Such investigation is beyond the scope of this work.

There may be a concern regarding the effects of routine works that are repeated everyday. The large fluctuations observed around from 19:00 to 21:00 in Fig. 3 are suspected to be such activities, since they are observed repeatedly in the next day. This can be interpreted as a 24hrs. cycle even it is not produced by a physiological state but by actual life activity. Therefore, to avoid this confusion, data should be processed with each 24hrs. period. The wavelet decomposition can separate these effects if they are short-term events. The residual profile didn't indicate any effect from such activities, as shown in Fig 6.

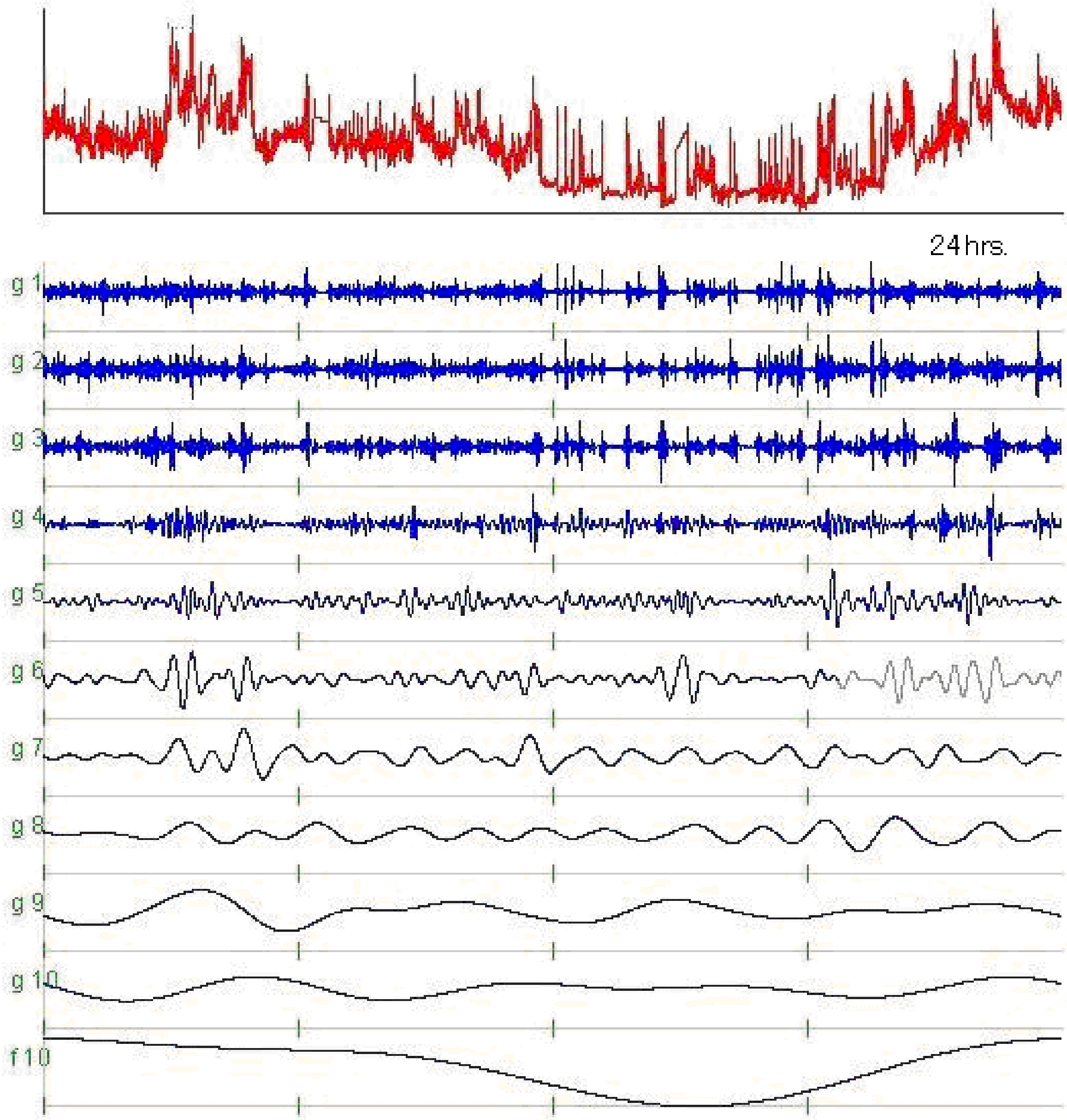

Fig. 6. Wavelet Decomposition Result for Heart Rate

Figure 7 reveals the decomposition results of body temperature. Although it is subjected to much higher noise and interruption than those of heart rate, range filtering/recreation and interpolation techniques can detect the daily state change as shown in Fig.7. A 24hr. block of data from 13:00 to 13:00 was chosen for analysis from the raw data shown in Fig.5. The large corrupted periods from 21:00 to 0:00 and after 12:00 were handled before the wavelet decomposition. The recovery procedure was applied to these areas to recreate the data.

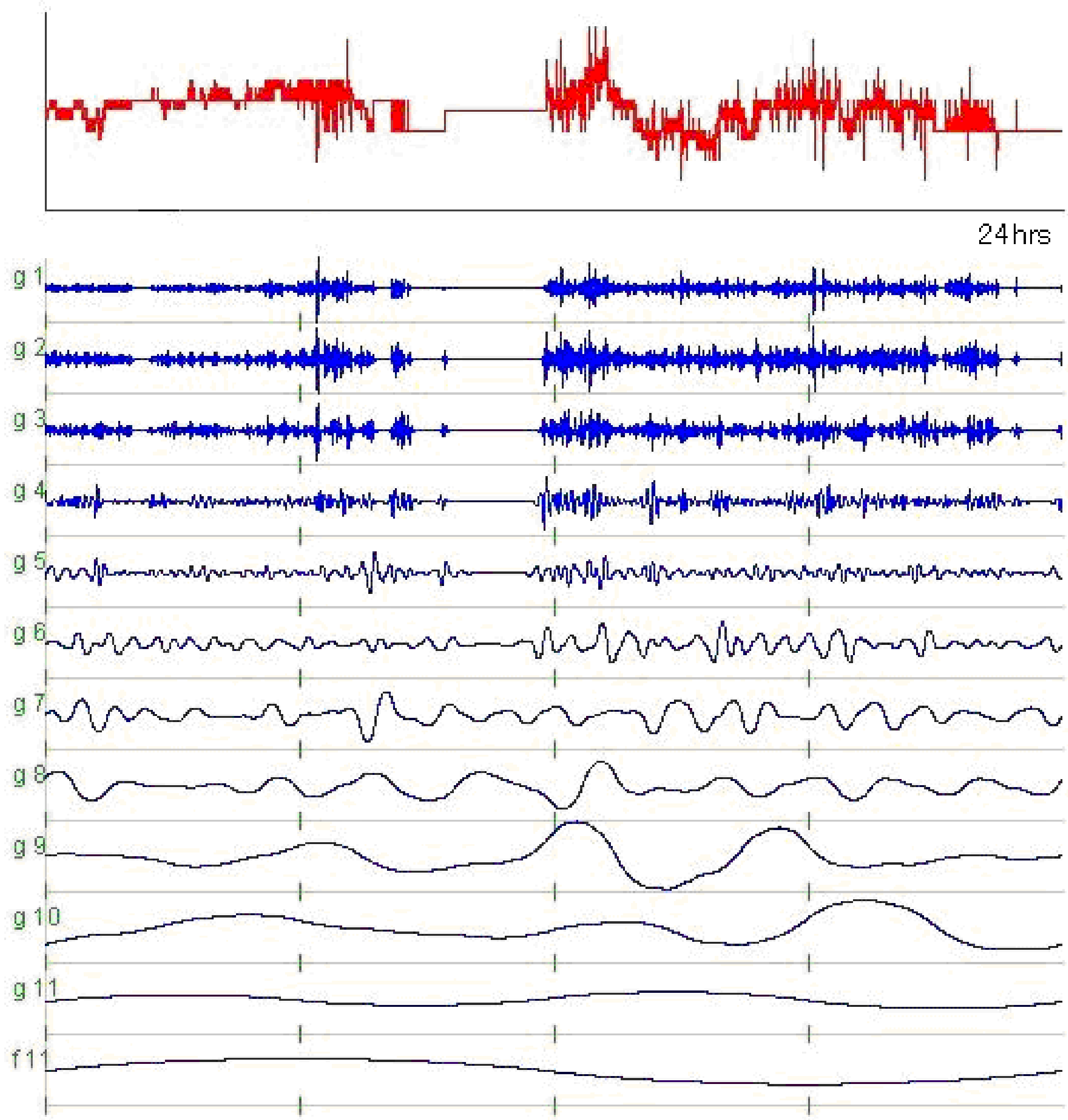

Fig. 7. Wavelet Decomposition Result for Body Temperature

The recovery process also worked for areas other than these large areas of damage when detecting data beyond the range filtering criteria. To examine the capability of the wavelet approach, we didn't execute any averaging process prior to the wavelet analysis, but employed the interpolation using the adjacent two points to create binary data points required for wavelet analysis. It is also applicable to use averaging process prior to the wavelet analysis by examining the noise floor characteristics of the sensor and electronics system. Averaging process is commonly implemented in temperature sensors for health care or medical use to garner a stable measurement. Since the application inherently assumes heavy data fluctuations, averaging should be executed sparingly so as not to convolute erroneous data into the analysis.

5.1 Body State Change

For physiological body response, the sleep and awake states are assumed to be important and are the focuses here. Medical research shows that heart rate slows during sleep, with periodical REM (Rapid Eye Movement) sleep activity inducing faster heart rates. To identify sleep disorders or to monitor the level of attention or drowsiness, cyclical body data can be helpful if significant circadian profile change is observed. Body temperature fluctuations are also a signature of the sleep state.

In the data presented, the subject who is a college graduate student aged 25 normally sleeps from 2AM to 10AM. The measurements were taken during normal days at college. When tracking physiological signatures, there are time differentials experienced. For this example, when entering sleep, the heart rate dropped first, followed significantly later by the body temperature. Each individual will respond differently. It requires more subjects and measurements to understand the relation between heart rate and body temperature in terms of physiological state recognition. To verify which changes in state are authentic, continuous monitoring is required to extract patterns. Therefore, it is important to recognize a pattern of each person by routinely measuring and evaluating the state on daily basis.

5.2 Evaluation with Wavelet

Although heart rates and body temperatures show certain changes between the two states, profiling can be complicated, exacerbated by daily activities, sleep state changes including REM or other elements. The shape neither follows a specific waveform, nor is there a sudden change among states. Extracting physiological state information is inherently slow and usually does not show a specific waveform or frequency.

Assuming that the purpose is to differentiate state changes by applying wavelet analysis, residual profiling by eliminating short-term changes and noise is essential. It is noted that there is no specific selection of mother wavelet and decomposition levels to extract circadian profile. For example, if a profile exhibits steep step changes, the extraction of a step stage change profile with existing mother wavelets is difficult. Wavelet analysis for the typical function profile is investigated in Matlab Wavelet Toolbox User's Guide (Misiti et al., 2002).

The techniques introduced here aim to eliminate misleading or false artifacts when handling data being measured during daily life to identify daily physiological profile changes. The evaluation shall be proceeding step by step. Using the denoising process, wavelet distribution can be better clarified without being submerged by the noise. In the process of extracting a diurnal profile, different decomposition levels or mother wavelets can be tested within the framework of theoretical limits mentioned above. If remaining signature represents physiological significance, further investigation will be applied.

6. Conclusion

The study addressed herein focused primarily on the instruments and data processing techniques used on a human body to monitor physiological states during normal daily life (Yasui et al., 2008). Heart rate and body temperature were the two attributes measured for this study. The physiological or medical implications from this measurement and analysis are only discussed within the change of state during daily cycles. However, it was shown that the wearable electronics and wavelet computational techniques presented can extract physiological state from data points throughout the day. This gives us positive initial proof for the use of cybernetics in gathering physiological information towards developing a non-invasive daily health tracker to better grasp the general well-being of individuals. We suppose real-life monitoring is no less important than clinical diagnosis, when aiming to find a physiological signature, such as biological clock or sleeping disorder, derived from a personal attributes and experiences. Inherent difficulties and constraints with continuous around-the-clock monitoring are tackled by the techniques proposed associated with the wavelet data handling methods. The method is able to show obvious physiological changes, even when significant noise is present and data interruptions occur while taking measurements. Cybernetics for physiological understanding will further be developed in conjunction with the advancement of consumer electronics.

7. Acknowledgement

The author would like to extend his gratitude to all joint project members at the Information, Production and System Research Center of Waseda University, NTT DoCoMo Advanced Technology Research for test support, and Mr. Kevin Williams for editing this manuscript.

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Biomedical Engineering
Edited by Carlos Alexandre Barros de Mello

ISBN 978-953-307-013-1
Hard cover, 658 pages
Publisher InTech
Published online 01, October, 2009
Published in print edition October, 2009

Biomedical Engineering can be seen as a mix of Medicine, Engineering and Science. In fact, this is a natural connection, as the most complicated engineering masterpiece is the human body. And it is exactly to help our “body machine” that Biomedical Engineering has its niche. This book brings the state-of-the-art of some of the most important current research related to Biomedical Engineering. I am very honored to be editing such a valuable book, which has contributions of a selected group of researchers describing the best of their work. Through its 36 chapters, the reader will have access to works related to ECG, image processing, sensors, artificial intelligence, and several other exciting fields.

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