Characterization of Ultradian and Circadian Rhythms of Core Body Temperature Based on Wavelet Analysis

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Abstract—**This study was motivated by the needs of precise characterization for the ultradian and circadian rhythmicity of human core body temperature (CBT). The CBT data, two-whole-days' data of two female bed-ridden old aged suffering from cerebral infarction sequelae, was detrended to eliminate the long-term components with periods longer than two days and normalized at first. It was then analyzed by the stationary wavelets transform (SWT) to get the time-frequency information. In the step of SWT, *symlet* 6 was used, and the approximation waveforms in the 5th, 6th and 7th levels were used to reveal the targeted rhythmicity. The results of the SWT show that SWT can faithfully reveal the time-frequency information of feature elements (peaks and troughs) of waveforms and rhythmicity can be characterized by analyzing temporal information of feature elements.**

I. INTRODUCTION

In order to adapt themselves to the cycles of the environment, human beings have their own mechanism working and evolving, which makes their inherent biorhythms, e.g., circadian, lunar or annual rhythms.

A well-known important biorhythm is the so-called circadian rhythm, where circadian is from Latin meaning "about a day". The circadian rhythm [1] emanates from suprachiasmatic nucleus located in hypothalamus, and mediated by the secretion of melatonin [2]. Adverse consequences on account of mismatch between the endogenous biorhythm and the behavioral rhythms have been revealed by clinical trials [3], [4].

To identify the relationship between the behavior of biorhythm and some specific physiological consequence, one should determine the necessary information about the behavior pattern of biorhythms, e.g., the period, phase, etc.

Various analyzing methods, e.g., Fourier transform (FT), cosinor method (CM) [5], wavelet transform (WT) [6] maximum entropy spectral analysis (MESA) [7], have been proposed. Among these methods, FT is often obviated for deviation from the realistic spectrum caused by the necessary manipulation to the raw data.

Moreover, most kinds of biosignal are inherent non-stationary, which means that their amplitudes and frequency components vary temporally and individually. Periodogram calculated by MESA provides information about periodic components generally. However, it is not adequate in providing precise time-frequency information about component in a specified period.

On the other hand, circadian rhythm is closely related to aging, the diurnal cyclic behavior becomes blurry gradually [8]. Occasionally, circadian rhythm even gives its dominant place to ultradian rhythm [9]. In such kind of physiological data, multiple peaks and troughs are obvious and often randomly distributed during diurnal record. Therefore we need a precise and flexible method to tell us whether this fluctuation is significant or not so as to identify the pattern of biorhythm.

A proper approach for the non-stationary signal analysis is wavelet analysis, which is extensively used in the analysis of various kinds of biosignals [10], [11]. This method gives both temporal information and frequency information useful in the following analysis.

In this paper, we mainly adopted the discrete wavelets transform (DWT) to characterize the behavior of the core body temperature (CBT), whose rhythmicity is considered to be of special significance for physiological condition [12]. We carried out this study based on the finding during biorhythm analysis for continuous CBT signals, whose fluctuations show rhythmicity other than circadian rhythm. Before we can analyze the rhythmicity, we need to extract features, e.g., the amplitude and temporal location of the peaks and troughs (also denoted as feature elements hereafter), of the waveform of the signal.

The ultradian and circadian components were targets in this study. Two-whole-days' continuous CBT record from two bed-ridden old aged with cerebral infarction sequelae were used here. By this processing, we hoped to grasp the features of fluctuations in the periods of interesting.

II. METHODS

A. Subjects and Data

The two-whole-days' CBT data of two female bed-ridden old aged suffering from cerebral infarction sequelae, were used in this study.

Because the activities of the subjects were confined to bed, fluctuations of their CBT waveforms could be regarded as the appearances of their endogenous CBT rhythmicity. Moreover, patients with impairment of central nervous system were considered to have blurry circadian rhythms, which can be observed in Fig. 2 (a) and (b).

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Subjects were being monitored in ward during the measurement, so that stimulations to CBT from intake of food and ambient luminous intensity were also regulated. In this situation, Fluctuations of the CBT were considered to reflect the endogenous rhythmicity faithfully.

The CBT data was acquired by a noninvasive CBT thermometer (THM-003T, Citizen, Tokyo, Japan) every 3 minutes for 72 hours starting at 09:00 on the first day. However, only two-whole-days' data starting from 00:00 was shown in this study to take away the edge effect of DWT.

The measurements were approved by the Ethics Committee of Kanazawa University School of Medicine.

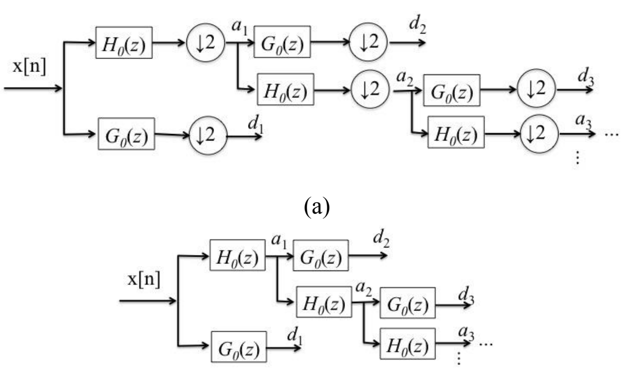
B. Wavelets Transform

In brief, continuous wavelets transform (CWT) convolves a temporal signal $x(t)$ with a scaled wavelet function $\psi(t)$, which is scaled by dilating and translating. By convolving with $\psi(t)$ of different scale, the $x(t)$ can be separated into different components:

$$W_s x(t) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t)\, \psi\left(\frac{t-a}{s}\right) dt, \quad (1)$$

where, s and a is the dilation and translation factor of the wavelet function $\psi(t)$, respectively. By enlarging s, $\psi(t)$ is dilated and result in a rougher approximation of the original signal. By increasing/decreasing a, $\psi(t)$ is translated to the right/left in the time axis.

For discrete signal x[n], the discrete wavelet transform (DWT), which is of different nature from CWT, is adopted. Instead of the wavelet function, a high-pass filter g_0 and a low-pass filter h_0 is used in cascade (Fig. 1 (a)) to extract the approximations and details of different period ranges.



(a)

(b)

Fig. 1. The cascade structure of (a) DWT and (b) SWT. The outcome at each level is decimated with a factor of 2 in DWT but conserved in SWT.

In the recursive procedure, approximation and detail waveforms are decimated by a factor of 2, which leading to the missing of odd-numbered components and finally the missing of the characteristic of time-invariance.

In the processing of CBT data, it was necessary to maintain the time resolution so as to get the accurate temporal information of the feature elements. To meet this requirement, stationary wavelet transform (SWT), also being well-known as à trous algorithm [13], is an appropriate approach. It has almost the same structure as the DWT, except for the removing of the downsampler in each level (Fig. 1 (b)). It is realized by upsampling the filters' coefficients by a factor of 2^{j-1} in the jth level.

C. Procedures

Before processing the signal using SWT, we should be aware of that the CBT signal contains not only the circadian and ultradian rhythmic components but also long-term components and random noise. The long-term components, e.g., the lunar component, would have substantial effect on the temperature value over a short period, e.g., one day. Hence, the process was implemented as follow.

- Detrend. Zero-phase filtering scheme with a 6-order Butterworth high-pass filter with 48-hours cutoff frequency was adopted. Zero-phase filtering was used to maintain the time-frequency characteristics of the signal. 48-hours cutoff frequency was used here because that it could remove the long-term trend in the waveform but retain most of the signal.
- Normalization. This study aimed at the variation of the CBT signal, hence we normalized the detrended temperature value with by

$$\mathrm{x_n}[\mathrm{n}] = \frac{(\mathrm{x}[\mathrm{n}] - \overline{\mathrm{X}})}{2\sigma}, \quad (2)$$

  where, x[n] and $\mathrm{x_n}[\mathrm{n}]$ is the detrended signal and the normalized data, respectively; $\overline{\mathrm{X}}$ and σ is the mean value and the standard deviation of the temperature data, respectively.
- SWT. In this context, we mainly used the approximation in the targeted levels to extract the characteristics of the fluctuation. Since the shape of the filter would affect the outcome, we chose *symlets* 6 [14], a near symmetric orthogonal wavelet, for the analysis.

TABLE I. THREE-DECIBEL CUTOFF PERIODS OF EQUIVALENT DECOMPOSITION LOW-PASS FILTERS CORRESPONDING TO 3-MINUTES SAMPLING INTERVAL

Scale 2^j	2^5	2^6	2^7
Cutoff period (Hrs)	6.3	12.6	25.7

- Targeted levels. The targeted levels of the SWT for analysis were decided by the period of interesting, which were ultradian and circadian components with period from about 6-hours to 24-hours. The 3-dB bandwidths of the equivalent decomposition low-pass filters corresponding to 3-minutes sampling interval are shown in Table I. We changed the bandwidths into corresponding periods here to go along with the context discussing the period of the signal.
- Characterization. The waveforms of targeted levels were characterized by their peaks and troughs. For these fluctuations, some subtle variation should be eliminated by thresholding so as to get a clear image. Assuming the distribution of the amplitude of peaks and troughs to be normal, the peak was eliminated if

$$p < \overline{A}_p - \sigma_p, \quad (3)$$

and trough was eliminated if

$$t > \overline{A}_t + \sigma_t, \quad (4)$$

where, p and t were the peak and trough to be eliminated. $\overline{A}_p$ and $\overline{A}_t$ were the mean amplitudes of peaks and troughs, and σ_p and σ_t were the standard deviations of the amplitudes of peaks and troughs.

III. RESULTS

This part shows the results by implementing preconditioning (Detrend, normalization), then SWT and finally characterization by feature elements.

A. Detrend and normalization

The raw CBT data of the two subjects are shown in Fig 2 (a) and (b), where obvious variation of temperature value that recurring within one day could been observed for both subjects. By the Butterworth high-pass filter, the long-term trend was removed and the baseline became stable. Fig 2 (c) and (d) show the detrended-normalized signals for the two subjects.

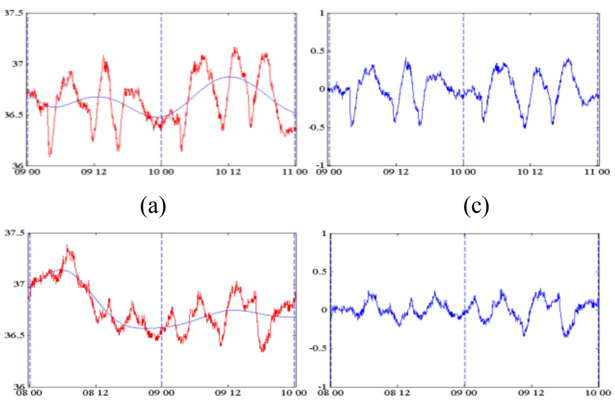

(a) (c)
(b) (d)

Fig. 2. Two-whole-days' raw, detrended signal and detrended-normalized waveforms of core temperature of two female subjects. Ticks in x-axis denote the time of the measurement in the form DD HH. For subject 1, red plot and blue curve in (a) show raw data and long-term trend respectively, while blue plot in (c) shows the detrended-normalized signal. Waveforms of subject 2 are shown by subfigures (b) and (d).

B. SWT

The approximation waveforms of the target levels were used for the successive characterization. Hence, only these waveforms are shown in Fig. 4 and Fig 5. In both figures, detrended-normalized CBT waveforms were plotted in the top subfigures, while approximation waveforms of level 5, 6 and 7 were plotted in the following subfigures.

C. Characterization

For each level of approximation, it was characterized by its peaks and troughs, which were picked out by comparing each data point with its adjacent points. Amplitudes of fluctuation in each level were shown by the amplitudes of peaks and troughs.

Since with the increasing of the level, the corresponding bandwidth of the will decreased, the waveform of level 6 contains component in level 7, and the waveform of level 5 contains components in level 6 and level 7. Components of higher frequency can be extracted in lower level.

For both subjects, the approximation waveforms of level 5 can reflect the major fluctuation in the raw data and give us additional information other than circadian components. For instance, 2ed and the 5th peaks in level 5 of subject 1 are obvious, however, could not be seen even in level 6.

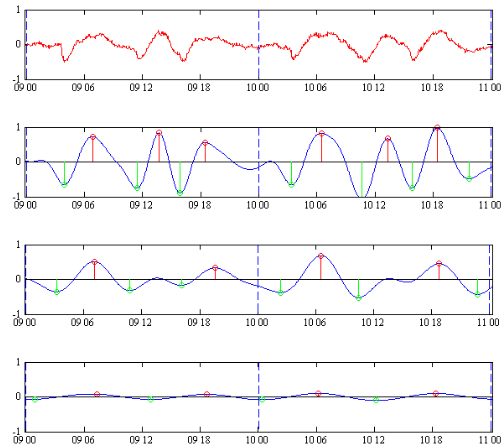


Fig. 4. Detrended-normalized CBT data and the approximation waveforms of level 5, 6 and 7 for subject 1. Corresponding waveforms are shown from top to bottom. Ticks in x-axis denote the time of the measurement in the form DD HH.

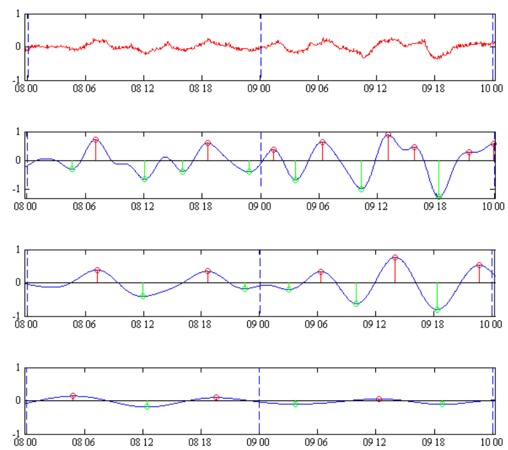


Fig. 5. Detrended-normalized CBT data and the approximation waveform of level 5, 6 and 7 for subject 2. Corresponding waveforms are shown from top to bottom. Ticks in x-axis denote the time of the measurement in the form DD HH.

While for subject 2, no distinct difference between level 5 and level 6 could be seen, even though some faint feature elements are revealed in level 5.

With the feature elements, the rhythmicity of the CBT could be characterized. For example, for the waveform of level 6 of subject 1, a circadian component can be seen with the recurring of similar peaks, i.e., the pair of the 1st and the 3rd peaks and the pair of 2ed and the 4th peaks. However, the circadian rhythm is vague for subject 2 in both waveforms of level 6 and 7.

IV. DISCUSSION

This study of applying the multi-resolution wavelet analysis to analyze rhythmicity of CBT was motivated by the problem arising in the application of the conventional CM to analyze the circadian and ultradian components. By using the CM, the overall features of the fluctuation, such as its mesor and its amplitude, can be calculated. However, more often than not, it can't give us the precise information about the peaks and troughs especially in the range of ultradian period.

Applying the SWT to the signal is actually applying the filters cascade to signal. Hence, frequency bands of approximations of consecutive levels are somewhat overlapped. With the increasing of the level, the waveform becomes fainter and fainter since information left becomes less and less with the passing-through of the low-pass filters. In this sense, it is better to choose a lower level for analysis. What is more, consideration about the frequency band of interesting should also be paid before deciding with level to analyze. We mainly focused on the components with periods longer than 6-hours in this study based on the visual judgment about the periods of the major components. We can and must adjust the targeted levels for the analysis of a specified biosignal.

Being more specific, subject 1 uptook the necessary nutrient by PEG (Percutaneous Endoscopic Gastrostomy) at 05:00, 11:00 and 17:00, while subject 2 uptook the nutrient by TPN (Total Parenteral Nutrition). Both subjects lived in wards where the illuminations were regulated at 2 periods one day, from 05: 00 to 07:00 and from 17:00 to 22:00. The CBT peaks in level 5 of subject 1 show good correspondence with the timings of nutrient intake, CBT reached its local maximum about one hour later. Moreover, the variation of CBT in level 6 may also hint the influence of the illumination. Same trend can be seen in subject 2, except the unexpected peak at about 14:00, 9th, in level 6. Compared with subject 2, the fluctuation of CBT of subject 2 seems more complicated. Sporadic local peaks exist and rhythmicity can hardly been seen in level 5. The TPN nutrient intake method may be a factor causing this disorder.

This study shows that by using SWT, the fluctuation of CBT signal can be described by the feature elements of waveforms of different frequency bands. However, how to use these feature elements is still to be answered. Since time-frequency information of the feature elements can be attained, it is plausible to combine the temporal information and the quantitative parameters, e.g., mesor or amplitude from CM, to classify the rhythmicity of CBT.

V. Conclusion

In order to characterize the ultradian and circadian rhythms of the continuous core body temperature signal, a kind of non-stationary signal, this paper used the stationary wavelets transform to get time-frequency information. The results of the analysis show that, SWT can faithfully reveal the peaks and troughs of waveforms with frequency bands of interesting. Rhythmicity can be characterized by analyzing this temporal information.

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