Estimation of a Menstrual Cycle by Covariance Stationary-Time Series Analysis on the Basal Body Temperatures

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***Abstract*—The daily recording of a woman's basal body temperature is the most easy and convenient method for estimating ovulation period especially by resolving the biphasic trend in the temperature readings. For this study, a woman's basal body temperature data are collected on a daily basis and interpreted as a time series-data to discern the periodicity in terms of a menstrual cycle. A new method of detecting the cycle is proposed with estimating the sample autocorrelation function as a time-domain decisive feature and with computing its power spectral density by periodogram in a frequency-domain aspect.**

***Index Terms*—basal body temperature, menstrual cycle, ovulation, discrete fourier transform, Autocorrelation, Power Spectrum, Time series, periodogram.**

I. Introduction

Concerning the enhancement of a woman's fertility awareness, the very important attention is to estimate the ovulation time with a personal effort. Several methods were sought to guess the best time for the future fertility: (i) referring to the average number of days in the past cycles to evaluate the time of ovulation time as two weeks prior to the beginning point of the period (ii) monitoring the progressive phase of cervical mucus [1] (iii) charting Basal Body Temperature (BBT) and identifying its biphasic pattern as a temperature-spike in which body temperature decreases before ovulation and rises afterwards [2]. Although all of these methods are not suitable for predicting the exact-onset of ovulation time, they might still offer helpful information to increase a woman's fertile activity. As far as checking her ovulation status with a personal effort, the most easy and convenient way is to estimate the exact menstruation period. Accordingly, the aim of this study is to assess a menstrual cycle as a component of fertility awareness by applying time series analysis on the BBT data. For the experimental simulations, two females' basal body temperatures are measured on a daily basis and interpreted as a time series-data to discern the periodicity in terms of a menstrual cycle. Assuming that the basic trend of such a time series data does not change drastically in time, a sample autocorrelation function is calculated to estimate the cycle as a time-domain decisive feature and Discrete Fourier Transform (DFT) and periodogram [3] with a frequency resolution of $1/N$ Hz (N is the total number of sample points consisting of the time series) are also computed to resolve the DC level and dominant frequency in terms of mean body temperature and a menstrual cycle.

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II. Acquisition of BBT Time Series Data

BBT is the lowest body temperature which is generally measured right after awakening without undertaking any physical activity including eating, drinking or going to the bathroom [4]. For our experimental simulations, two healthy female subjects (21 and 23 years old, respectively) were volunteered and provided written informed consent. They followed the instructions [5] how to take and record their BBT in Celsius temperature scale on a daily basis using a digital-ear thermometer (BT-020, Easytem, Korea) embedded with an infrared filter. Its temperature resolution is 0.1° c. The collection of BBT is interpreted as a time series data with the normalized sampling frequency of 1 Hz. Fig. 1 shows the visualization of BBT time series data measured from subject A and B.

According to the self-reported menstrual cycle, subject *A* gave us advance notice of her cycle with a period of 34 or 35 days while subject *B* informed the irregularity in

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her menstruation cycles – tendency of skipping menstruation for two or three months after the initial period has ended.

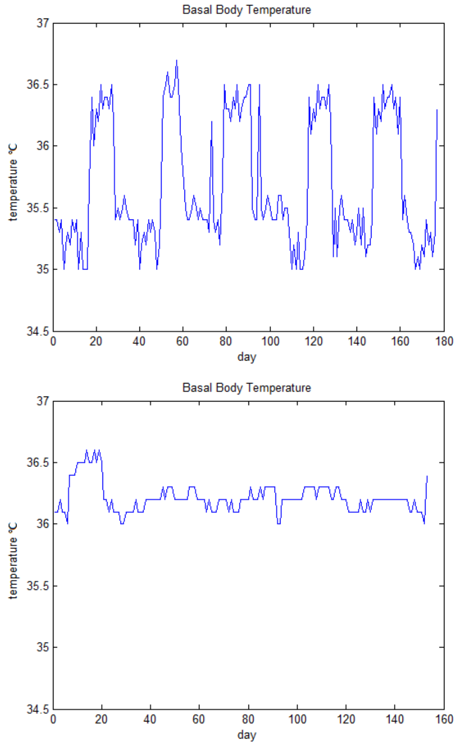

Figure 1. BBT time series data measured from subject A (top) and B (bottom)

III. Assessment of Menstrual Cycle in Time Domain Feature

Assuming that the basic trend of BBT time series does not change drastically in time, a sample autocorrelation function can be calculated in covariance-stationary sense. The sample autocorrelation [6] is a time-domain feature in which the time series is self-aligned and multiplied by itself with varying time delay from 0 to the duration of the data. For the computation, a sample mean of the discrete BBT time series data $[x_1, x_2, ... x_N]$ is primarily estimated by

$$\bar{x} = \left(\frac{1}{N}\right) \cdot \sum_{i=1}^{N} x_i \qquad (1)$$

With assumption of wide-sense stationary in BBT time series, the sample auto-covariance, γ_k, is defined with k-delays by

$$\hat{\gamma}_k = \left(\frac{1}{N}\right) \cdot \sum_{i=1}^{N-|k|} (x_i - \bar{x}) \cdot (x_{i+|k|} - \bar{x}),$$

$$k = 0, \pm 1, \pm 2, \ldots, \pm(N-1) \qquad (2)$$

The sample autocorrelation function, ρ_k is the normalized version of auto-covariance function such that

$$\rho_k = \frac{\gamma_k}{\gamma_0} \qquad (3)$$

$$where, \quad \gamma_0 = \left(\frac{1}{N}\right) \cdot \sum_{i=1}^{N} (x_i - \bar{x})^2$$

The menstrual period is resolved by the nonzero delay that results in the second largest peak in the sample autocorrelation function. Fig. 2 illustrates the computation result of sample autocorrelation function that depicts the largest value at k = 0 and the second largest peak at a certain lag for subject A and B, respectively.

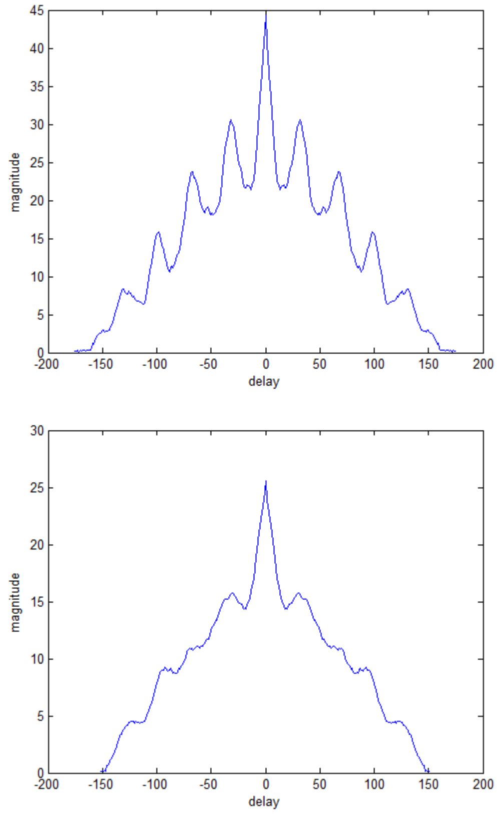

Figure 2. The sample autocorrelation function for subject A (top) and B (bottom)

IV. Estimation of Menstrual Cycle in Frequency Domain Feature

Alternative approach to estimate the periodicity in BBT time series data is referring to the detection of a dominant frequency. In this sense, the relevant information concerning cyclic trend in time series data can be transferred into frequency domain by performing DFT as a primary frequency-analysis tool. The secondary tool is also considered by computing periodogram to estimate power spectrum.

A. Estimation of a Menstrual Cycle by DFT

Using the same time series data (the sampling frequency is normalized by 1 Hz) that was used for the sample autocorrelation computation, DFT is calculated by

$$\mathrm{X(k)} = \left(\frac{1}{\mathrm{N}}\right) \cdot \sum_{\mathrm{i=0}}^{\mathrm{N-1}} \mathrm{x_i} \cdot \mathrm{e}^{-\mathrm{j}\left(\frac{2\pi}{\mathrm{N}}\right)\mathrm{ki}}$$

$$0 \leq \mathrm{k} \leq \mathrm{N}-1 \tag{4}$$

In Fig. 3, the amplitude spectrum of DFT for the same subject *A* and *B* are shown (frequency range is visualized from 0 to 0.5 Hz) in dB scale due to the very large DC level relative to the values at nonzero frequencies. The sampling frequency is normalized to be 1 Hz and consequently folding frequency becomes 0.5 Hz. The average body temperature over the entire BBT series data is determined by DC level and the menstrual cycle is estimated by a reciprocal number of a certain frequency in which the second largest peak has occurred. Fig. 3 shows that the average body temperature over the considered BBT time series for subject *A* is 35.6802℃ while subject *B* has 36.2144℃.

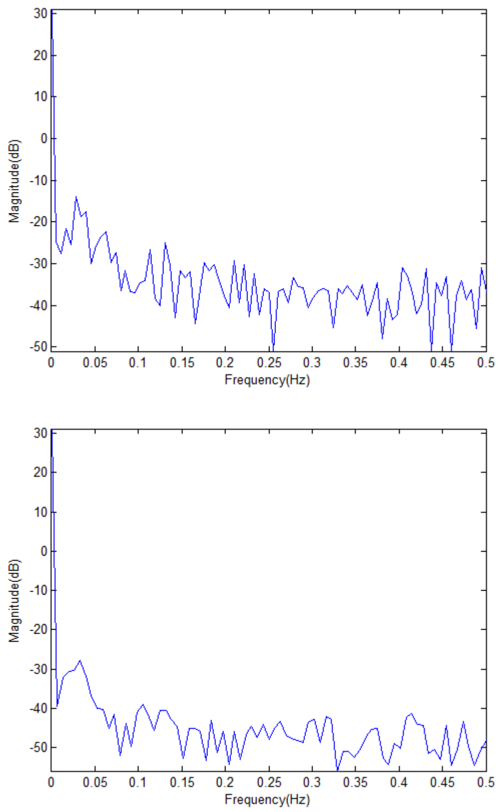

Figure 3. Amplitude spectrum of DFT in dB scale for subject *A* (top) and *B* (bottom)

B. Estimation of a Menstrual Cycle by Periodogram

Periodogram method is to estimate power spectrum especially evaluated at the harmonics of the fundamental frequency [7]. Throughout considering *N*-samples of BBT time series data with the normalized frequency of 1 Hz, the fundamental frequency f_1 is 1/*N* Hz. Thus the *i*th harmonics, f_i is defined by

$$f_i = \frac{i}{N}\, Hz, i = 1, \ldots, \frac{N}{2}\ (N\ is\ even) \tag{5}$$
$$= \frac{i}{N}\, Hz, i = 1, \ldots, M\ (N\ is\ odd,\ \ N = 2M+1)$$

In order to find the largest peak in periodogram-based estimation of power spectrum, a detrending method [8] is applied first to BBT series data to block the frequencies smaller than 0.011 Hz. The power spectrum *S*(*f*) is then calculated as

$$S(f_i) = \frac{1}{N}\left|\sum_{n=1}^{N} x_n \cdot e^{-j(2\pi f_i)n}\right|^2 \tag{6}$$

Alternatively equation (6) can be expressed by auto-covariance term [7]:

$$S(f_i) = \hat{\sigma}_x^2 + 2 \cdot \sum_{k=1}^{N-1} \hat{\gamma}_k \cdot cos(2\pi f_i k) \tag{7}$$
$$where, \quad \hat{\sigma}_x^2 = \hat{\gamma}_0$$

In computing periodogram, the spectral leakage problem might occur because the variance of the sample auto-covariance is getting larger especially when time delay approaches *N*. This leakage problem can be mitigated by multiplying periodogram with window function, *W*(*k*). To reduce the spectral-leakage artifact in estimating periodogram, Parzen window function is used by computing

$$W(k) = \begin{cases} 1 - 6 \cdot \left(\frac{|k|}{L}\right)^2 \cdot \left(1 - \frac{|k|}{L}\right), & |k| \leq \frac{L}{2} \\ 2 \cdot \left(1 - \frac{|k|}{L}\right)^3, & \frac{L}{2} \leq |k| \leq L \\ 0, & elsewhere \end{cases} \tag{8}$$

where *L* is the length of window function. Due to the limited number of samples in BBT series data, *L* is chosen to be *N*.

Fig. 4 plots the estimated power spectrum by applying Parzen window-function periodogram method for the same subject *A* and *B*.

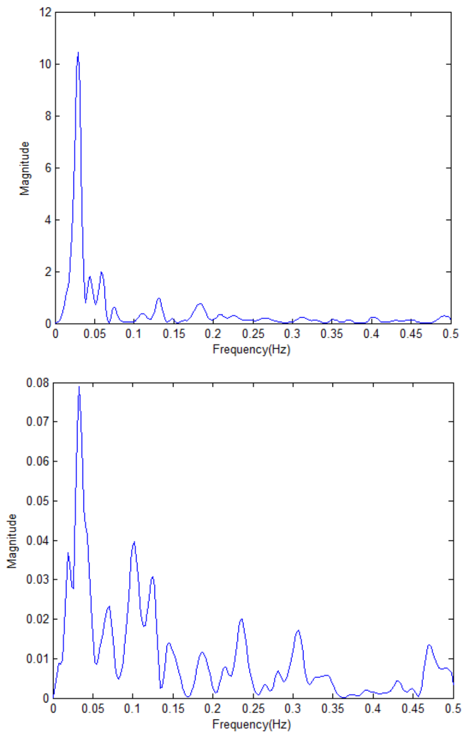

Figure 4. Estimated power spectrum by Parzen window-function periodogram for subject *A* (top) and *B* (bottom)

V. CONCLUSIONS

Table I summarizes the estimated menstrual cycle for subject A and B by computing autocorrelation, DFT and Parzen window-function periodogram, respectively.

TABLE I. THE ESTIMATED MENSTRUAL CYCLE

	Estimated menstrual cycle [days]		
	DFT	Auto-correlation	Periodogram
Subject A	35.2113	32	34.1297
Subject B	30.3951	31	30.1205

From our experimental simulations, we can conclude that a menstrual cycle can be estimated by interpreting BBT values as a covariance-stationary time series data and computing its pulse peak feature in time-domain (sample autocorrelation) or frequency-domain (DFT and periodogram), respectively.

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