Chapter 1
Prediction of Menstrual Cycle Phase by Wearable Heart Rate Sensor

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ABSTRACT

The prediction of the menstrual cycle phase and fertility window by easily measurable bio-signals is an unmet need and such technological development will greatly contribute to women's QoL. Although many studies have reported differences in autonomic indices of heart rate variability (HRV) between follicular and luteal phases, they have not yet reached the level that can predict the menstrual cycle phases. The recent development of wearable sensors-enabled heart rate monitoring during daily life. The long-term heart rate data obtained by them carry plenty of information, and the information that can be extracted by conventional HRV analysis is only a limited part of it. This chapter introduces comprehensive analyses of long-term heart rate data that may be useful for revealing their associations with the menstrual cycle phase.

INTRODUCTION

Although the menstrual cycle is a major biorhythm that governs biological functions of women, it is not easy to know the exact cycle phase like those of circadian and circaseptan (weekly) rhythms (Goodale et al., 2019). The most accurate method to detect the ovulation is transvaginal ultrasound examination (Ecochard, Boehringer, Rabilloud, & Marret, 2001), but it requires clinical visits and considerable cost. Calendar method and basal body temperature have been widely used, but the former is confounded by physiological cycle variation (Fehring, 2005) and the latter is affected by environmental temperature

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(Shilaih et al., 2018). Cervical mucus monitoring is inconvenient and subjective (Brezina, Haberl, & Wallach, 2011). Although urine-based luteinizing hormone (LH) can be used for detecting LH surge usually followed by ovulation within 2 days (Behre et al., 2000), it already misses the days with the highest conception probability.

A simpler and accurate prediction of the menstrual cycle, especially fertile window and menstrual periods, will further improve the quality of life for women and their partners. The development of useful methods is an important and challenging issue for information technology. This chapter discusses biological signal processing to predict menstrual cycle phases, focusing on heart rate signals that can be obtained from many popular wearable sensors.

HEART RATE VARIABILITY (HRV)

It is well known that the autonomic nervous functions in women are affected by the menstrual cycle. Many studies reported the changes in autonomic indices of heart rate variability (HRV) with menstrual cycle (Bai, Li, Zhou, & Li, 2009; Brar, Singh, & Kumar, 2015; de Zambotti, Nicholas, Colrain, Trinder, & Baker, 2013; Guasti et al., 1999; Leicht, Hirning, & Allen, 2003; Sato & Miyake, 2004; Sato, Miyake, Akatsu, & Kumashiro, 1995; Yildirir, Kabakci, Akgul, Tokgozoglu, & Oto, 2002). These studies commonly suggest that, compared to the follicular phase, the luteal phase is accompanied by relative increase in sympathetic activity to cardiac parasympathetic activity. These studies, however, have not yet reached the level that can predict the phases of the menstrual cycle and they have used short-term HRV obtained under well controlled laboratory conditions.

The analysis of HRV is divided into short-term and long-term HRV (Hayano & Yuda, 2019). Typically, the former uses 5-minute data and the later uses 24-h data, but the difference is not only the length of data. Short-term HRV is analyzed from data obtained in a laboratory under strictly controlled conditions, while long-term HRV uses data recorded by wearable sensors in freely moving subjects. The autonomic nervous system is constantly regulating the body systems in response to various external and internal stimuli. Thus, the autonomic indices of HRV also respond sensitively to measurement conditions. For example, the power of high frequency (HF, 0.15-0.4 Hz) component of HRV that reflects cardiac parasympathetic function increases with supine rest and non-REM sleep (Hayano & Yasuma, 2003) and it decreases with standing (Pomeranz et al., 1985), physical activities(Yamamoto, Hughson, & Peterson, 1991), and food intake (Hayano et al., 1990). The HF power is also affected by respiration independently of autonomic neural activity; it increases with slow and deep breathing (Hayano, Mukai, et al., 1994; Hirsch & Bishop, 1981). Also, low frequency (LF, 0.04-0.15 Hz) component, particularly its ratio to HF power (LF/HF), increased with standing (Hayano et al., 2001).

These indicate that conventional autonomic indices such as HF and LF power and LF/HF observed in long-term HRV do not reflect *autonomic function*, but they reflect *autonomic state* as a result of responses to certain stimuli (Hayano & Yuda, 2019). Even if the power of HF component was measured by long-term HRV analysis, it is impossible to interpret cardiac parasympathetic nerve function without information on the subject’s physical and mental states and measurement environment. Even if 24-hour average LF/HF is higher in subject A than subject B, it may not indicate a difference in autonomous function between subjects, but may be the result of subject B lying longer than subject A during recording (Yoshida et al., 2016).