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プライバシー保護したIoTモバイルヘルス心拍変動及び睡眠段階の周波数解析に関する考察

黄　緒平[1,a)]　菊池　浩明[2,b)]　范 俊逸[3,c)]

概要：近年，睡眠における質の定量分析及び睡眠時のストレス推定が注目されている．従来ではピッツバーグ質問票による睡眠の質の主観評価が主であり，ストレス推定には心電図の周波数解析が広く用いられるが，脈波測定時呼吸数や体動の制限により，睡眠時の自由測定が困難である．また，心拍変動による時間依存睡眠段階遷移に関する研究も行われているが，睡眠時の心拍数と睡眠段階間の相関の解明が課題となっている．本報告は腕型ウェアラブル IoT 機材を用いて採集した睡眠時心拍数と睡眠段階データを対象に自律神経バランス評価指標を用いてストレス推定および相関分析を行う．更に，プライバシー保護を目的として加法準同型暗号手法による解析を試みる．

A study on privacy preserving spectral analysis using IoT mHealth heart rate variability and sleep quality data

Xuping Huang[1,a)]　Hiroaki Kikuchi[2,b)]　Chun-I Fan[3,c)]

Abstract: In recent years, quantitative analysis of sleep quality and stress estimation during sleep have been important social issues due to sleep deprivation. Conventionally, sleep quality is mainly subjectively evaluated by pittsburgh questionnaire, while stress is estimated by power spectral analysis of electrocardiogram. However, measurement is difficult during sleep since restrictions on respiration rate and body motion. Sleep depth transition presumable by heart rate variability is achieved, however, the correlation between heart rate and sleep quality during sleep is not clarified. In this report, stress estimation during sleep by autonomic balance evaluation index and correlation analysis are performed to heart rate and sleep depth data collected by wearable IoT equipment. Furthermore, homomorphic cryptography is applied to analysis considering privacy preserving.

Keywords: wearable IoT, stess estimation during sleep, privacy preserving

1. Introduction

Sleep deprivation has been a social problem and an important issue for research on both of IT and metabolome pathological analysis. Conventional works indicate stress affect sleep quality[1], [2], [3]. IoT devices based research on relationship between heart rate variability (HRV) and autonomic nerve activity has been focused [4]. In [4], the relationship between heart rate and sleep states in camp has been investigated using subjective sleep states data collected by pittsburgh questionnaire. Power spectral density (PSD, $[ms^2/Hz]$) analysis of heart rate has been used as the stress index to calculate the ratio between low frequency (LF) component and high frequency (HF) component. The same index is widely used to estimate autonomic nerve (stress index) in conventional works [3], [5], [6], [7], [8], [9], [10].

1 明治大学 研究・知財戦略機構 Strategic Coordination of Research and Intellectual Properties, Meiji University
2 明治大学　総合数理学部 School of Interdisciplinary Mathematical Sciences, Meiji University
3 国立中山大学 資訊工程学系　Department of Computer Science and Engineering, National Sun Yat-sen University
a) huang_xp@meiji.ac.jp
b) kikn@meiji.ac.jp
c) cifan@cse.nsysu.edu.tw

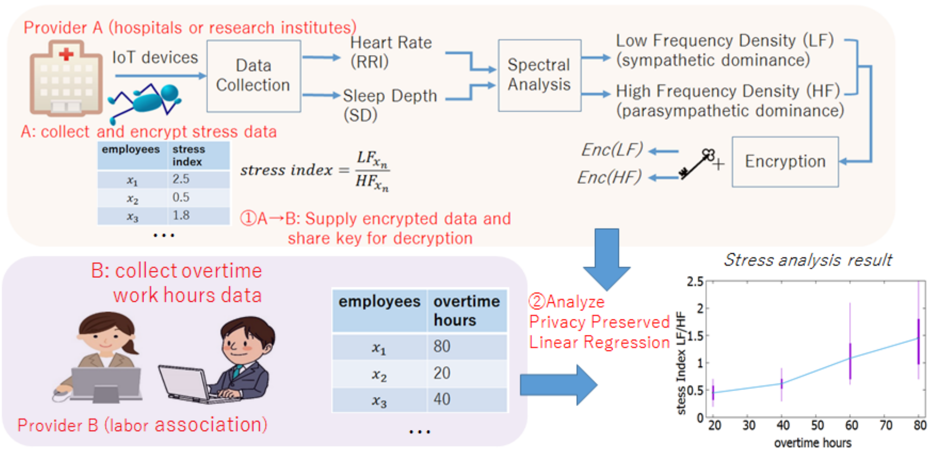


図 1 Target application: stress analysis with distributed and encryped data

For heart rate, in conventional works, RRI (RR Interval), collected via electrocardiogram (EGC) is used for analysis. According to manual [11], in order to avoid arrhythmic heartbeat of RRI, body motion and deep respiration are not allowed. Yoshida et al. [12] also suggested the respiratory sinus arrhythmia (RSA), which indicates breathing, implies a strong correlation to heart rate by analyzing PSD. Since breathing and body motion are difficult to be controlled during sleep, heart rate collected from EGC may result noise. Thus, to collect HRV (bmp: beats per minute) during sleep correctly, a more suitable device, which is unaffected by breath or body motion, is required. A wearable IoT device, which collects sleep depth, has been an alternative solution.

For sleep depth, Takeda et al. [13] proposed a model to estimate transition of sleep depth by analyzing heart rate variability and sleep duration. For this inference, a strong correlation between heart rate and sleep stage is required and has been an indispensable prerequisite. However, in the conventional works, the correlation between heart rate and sleep depth is not revealed.

Furthermore, confidentiality of sensitive personal information, including health monitoring systems has been an important issue [14]. However, it is not considered in the conventional works when analyzing biological information for stress estimation. As an alternative solution to privacy preserving, Ma et al. proposed a simple, but effective security solution for ECG signals based on an ECG compression algorithm [15]. However, the security against attack is not robust enough. Kikuchi et al. proposed a privacy preserving method to medical data by applying homomorphic cryptography to distributed dataset from different hospital and analyze the logistic regression to encrypted data to analyze real medical dataset [16], [17].

The final aims of this project are: (1) to disclose an appropriate indicator for sleep quality, (2) to clarify correlation between heart rate and sleep depth, and (3) to give a proposal to achieve confidential data processing and analysis using homomorphic cryptography for real biometric dataset collected by IoT devices.

As the contribution of this paper, we collected real dataset of heart rate and sleep depth data during sleep via wearable IoT device, and then we applied PSD analysis to the real data to analyze sleep quality by autonomic nerve as a stress index rather than subjective questionnaire or estimated from HRV. We examined PSD results of heart rate and sleep depth data collected by different IoT devices and disclosed which data is more appropriate to analyze sleep quality. Correlation between heart rate and sleep depth is also clarified through our experiment and analysis. Additionally, privacy preserving is considered to protect sensitive personal data.

As a preliminary preparation for privacy preserving, this report supplied a privacy preserving analyzing process through cryptological protocol between distributed institutes. Figure 1 illustrated a target application of this paper. A privacy preserving stress analysis is archived by a new protocol between hospital A, who owns the sensitive stress index, and the labor association B, who maintains the overtime history for employee. The stress of employees is identified through linear regression towards encrypted stress index and overtime hours to prevent suicide without using vulnerable plain data. Homomorphic property of public-key encryption allows to perform any analysis without revealing the confidential data.

2. Spectral Analysis on Heart Rate and Sleep Depth Data

2.1 Heart rate and sleep depth data

In conventional works, RRI value from EGC is used to analysis stress via PSD and to estimate sleep depth combing with sleep duration [13].

Sleep depth is usually defined to be Non-rapid-eye-movement (NREM) sleep and REM sleep to show sleep depth into different stages. Beth et al. divided REM and NREM into NREM 1-4 [18]; Huupponen et al. divided sleep depths into 6 stages as: W (wake), REM, S1 (light sleep), S2, S3, S4 (deep sleep) [19]; Takeda et al. divided sleep stages into 3 depths: wake, REM, and NREM [13].

Jawbones sleep coach report pointed out that deep sleep repairs muscles, and fights diseases, while REM sleep optimizes concentration, consolidates memories and organizes learnings when we dream [20].

As the relationship between heart rate and sleep depth, it is figured out that during REM sleep, heart rate is fairly irregular. Deep sleep has slightly more physical movement but a very steady heart rate. Light sleep is associated with more movement [20].

In this work, according to Jawbone's wearable IoT multi-sensor technology in UP3, it seeks out the unique physical characteristics associated with *Wake, REM, Light* and *Deep sleep* without uncomfortable electrodes capturing eye movement and brainwave, then classifies the sleep accordingly. For quantitative analysis, sleep depth is marked with numbers for four sleep depths captured by jawbone UP3 with sleep duration as: *4. Wake 3.REM 2. Light 1. Deep sleep* [20].

2.2 Spectral analysis for stress estimation

PSD shows the strength of the variations in frequency domain. By investigating the density of a certain power value and by analyzing the specific frequency range where

図 2 IoT devices to collect heart rate and sleep depth data during sleep

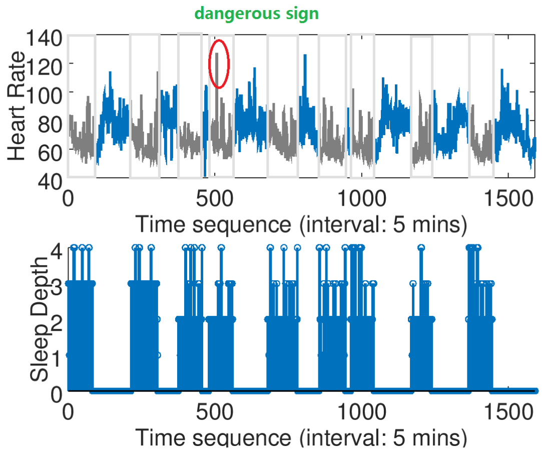


図 3 Heart rate and sleep depth data in June

the peak power located in, it will be a useful index as the health indicator. Computation of PSD is calculated by fast Fourier transform (FFT) of autocorrelation.

Spectral power between [0.04, 0.15] Hz indicates LF power (ms^2), while [0.15, 0.4] Hz indicates HF power (ms^2); and LF/HF ratio evaluates stess as the autonomic balance evaluation index [4], [5], [6], [7], [8]. Sleep apnea typically associated with spectral power oscillations between [0.01, 0.04] Hz, which may indicated heart disease or apnea syndrome as a dangerous sign. According to work [7], healthy and younger participants has higher RRI and RSA shows a more obvious peak in high frequency. Generally, power of HF get larger during sleep than daytime, which indicates parasympathetic nerve activity. Thus, a good sleep quality may have higher HF value, lower LF and LF/HF values.

2.3 PSD based on Wiener-Khintchine Theorem

According to Wiener-Khintchine Theorem, PSD function can be obtained by computing Fourier transform of autocorrelation function of a signal [21]. Periodogram, a onesided Fourier Transform is used to calculate PSD, and hamming window with length of 64 is applied to $x(t)$.

Autocorrelation function $C(\tau)$ measures the linear correlation between two variables $x(t)$ and $x(t+\tau)$. It is an even function on variable of time-lag τ with $C(0)$ as the maximum value and correlation gets weaker if τ gets larger. According to Ergodic Theory, autocorrelation of $x(t)$ is defined to be:

$$C(\tau) = \overline{x(t)x(t+\tau)} = \lim_{T\to\infty} \frac{1}{T} \int_{\frac{T}{2}}^{-\frac{T}{2}} x(t)x(t+\tau)dt \quad (1)$$

Here, T is the periodic variable and $-\frac{T}{2} < t < \frac{T}{2}$.

Suppose $X(\omega)$ is the Fourier transform coefficient of

$x(t)$, then FFT and inverse FFT are represented as follows:

$$x(t) = \int_{-\infty}^{\infty} X(\omega) e^{i\omega t} d\omega \quad (2)$$

$$X(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} x(t) e^{-i\omega t} dt \quad (3)$$

, here $\omega = \frac{2\pi}{T}$.

Power spectral $S(\omega)$ can be obtained by processing FFT to autocorrelation function $C(\tau)$ as:

$$S(\omega) = \lim_{T\to\infty} \frac{2\pi |X(\omega)|^2}{T} \quad (4)$$

2.4 Calculation of stress index

Heart rate converted to RRI and sleep depth values are used to estimate stress felt during sleep. LF value is calculated as follows:

$$\begin{aligned} P(\omega)_{LF} &= \int_{0.04}^{0.15} S(\omega) * \frac{\Delta\omega}{2} d\omega \\ P(\omega)_{HF} &= \int_{0.15}^{0.4} S(\omega) * \frac{\Delta\omega}{2} d\omega \end{aligned} \quad (5)$$

,where $\Delta\omega = \frac{1}{length(\omega)}$, and stress index is estimated by

$$ratio = \frac{P(\omega)_{LF}}{P(\omega)_{HF}} \quad (6)$$

In case that most of PSD values concentrated in higher frequency domain and peak value is detected in higher value, it indicated parasympathetic dominance. Oppositely, if the peak value of PSD located among LF domain, it indicated sympathetic dominance. The lower the *ratio* is, the more relaxing it indicated. Stress is estimated from result of *ratio* as defined in [22] that (1) *ratio* ∈[0, 0.8]: *relaxing*, (2) *ratio* ∈[0.8, 2]: *normal*; and (3) *ratio* >2: *stressful*.

3. Experimental result of stress during sleep

3.1 Dataset

Heart rate $x(t)$ $(x, t \in \mathbb{R})$ in time sequence is collected by Jawbone UP3 and Verifit ver.41 as plotted in Fig.2 for sleep depth (SD) and heart rate (HR) during 6/8-8/4, 2017 for 43 days, 5263 samples. Time t is with an interval around 5 minutes. The participant for the experiment is a 30's female, healthy with BMI=18.7. The statistics of data collected is listed in Table 1. RRI is calculated by $\frac{60}{x(t)} * 1000$ (ms).

3.2 Data analysis on heart rate and sleep quality during sleep

Examples of heart rate and sleep depth during 6/8-6/10

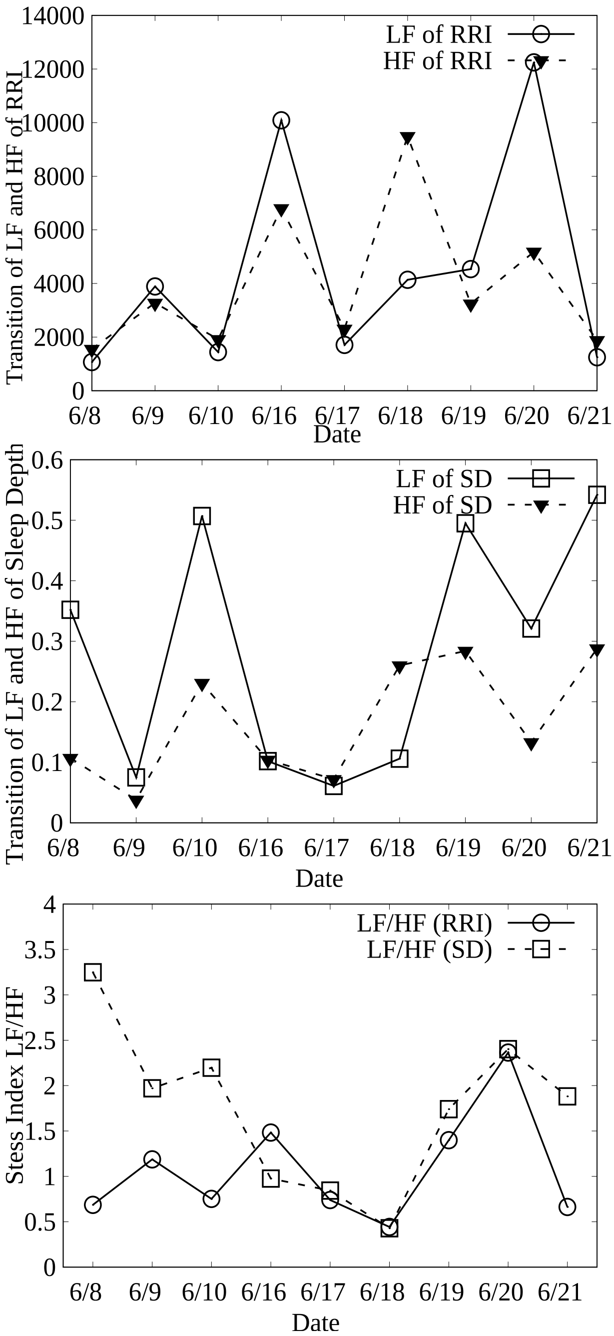


図 4 Transition of LF, HF, and stress index LF/HF radio of RRI and sleep depth

表 1 Statistics of heart rate and sleep depth data

Index	Value
$\overline{HR} \pm \sigma(bmp)$	70 ± 13.7
$\overline{RRI} \pm \sigma(ms)$	884 ± 162
$\overline{SD} \pm \sigma$	2.35±0.78
median, mode (HR)	68, 55
median, mode (SD)	2, 2
maximum, minimum (HR)	136, 41

and 6/16-6/21 are plotted in Fig.3. The gray components are heart rate during sleep while the blue components show heart rate during wake. It is obvious that heart rate values maintain to be lower during sleep than wake. Arrhythmic heartbeat, especially high value of heart rate and sudden upbeat may be observed if heart failure or sleep apnea occurs. $x_{507} = 127$ during light sleep may behavior disorder and should supposed to be a dangerous sign since the precipitous upbeat could be a relevant issue of breathe after apnea period. This signs should be focused if abnormal value appears frequently.

Theoretically, heart rate stays stable if sleep quality is good, otherwise, variability is more remarkable. Figures 5 and 6 show a correlated variability between heart rate and sleep depth accordingly to a stable and unstable HRV on 18th and 8th, June, which may indicate sleep qualities. Table 2 lists the details of sleep depth, sleep duration and heart rate to give a comparison between good and bad sleep qualities. As shown, good sleep quality is associated with sleep better stability and the slow oscillation, which is indicated in Figures.5 and 6 good sleep has slower heart rate and most of sleep depth concentrated around light sleep with longer deep and light sleep duration.

In order to verify whether the daytime activities affect heart rate during sleep, heart rate at 1 hour before sleep (average value of every minute) and average heart rate during sleep are listed and compared. Figure 7 plots the comparison result with 25 days' data. The average value of 1 hour before sleep and average value during sleep is 62 BMP and 57 BMP. It indicates that heart rate values stay stable and lower during sleep, while heart rate values at 1 hour before sleep decrease but are generally higher than average HRV during sleep, which are supposed to be affected by the daytime activities.

3.3 Result of power spectral analysis on stress

Formulas (5) and (6) are implemented to calculate LF, HF and LF/HF with onesided spectral power, in hamming window sized 64.

Figure 4 plots the transition of LF, HF and $ratio$ to estimate the sleep quality and stress index during sleep using data from 6/8 to 6/21 which include data approximately a circle of week.

According to Fig.4, in case of RRI, $LF > HF$ in 6/16 and 6/20, which obviously indicate stressful condition. $HF > LF$ on 6/18, which shows a relaxing condition. In case of sleep depth, a stressful condition is indicated on 6/8, 6/10, 6/19, 6/20 and 6/21 that $LF > HF$ is obviously shown, while on 6/18, a relaxing condition is shown that $HF > LF$. For both of RRI and sleep depth, data on 6/18 refers to a good sleep quality. In case of stress index, data on 6/18 has both of RRI and sleep depth a low $ratio$, while on 6/8, the $ratio$ of sleep depth is 3.279, which means a stressful condition. On 6/8, 6/10, 6/17, 6/18 and 6/21, data show a low $ratio$ value of RRI and on 6/16, 6/17, and 6/18, data show low $ratio$ value of sleep depth, which indicated a relaxing condition. How-

表 2 Comparison between sleep qualities on 8th and 18th June

Index	Stressful (8th June)	Relaxing (18th June)
$\overline{HR} \pm \sigma$	67± 9.87	61± 8.98
$\overline{SD} \pm \sigma$	2.81±0.79	2.12±0.80
median, mode (HR)	65, 60	59, 58
median, mode (SD)	3, 3	2, 2
deep sleep duration	43 mins	1h 35 mins
light sleep duration	12 mins	1h 30 mins
rem sleep duration	5h 16 mins	4h 21 mins
wake	1h 47 mins	35 mins
arousals (times)	3	3
total sleep duration	7h 22 mins	7h 27 mins

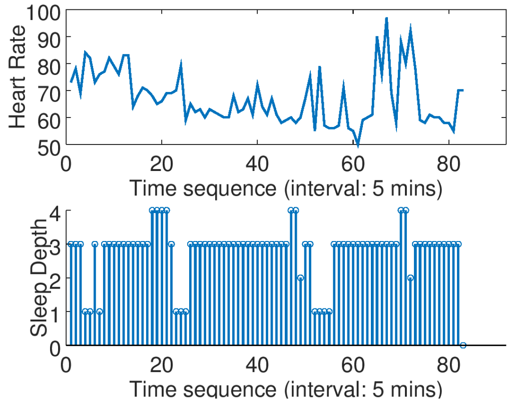


図 5 HRV and sleep depth on 8th June

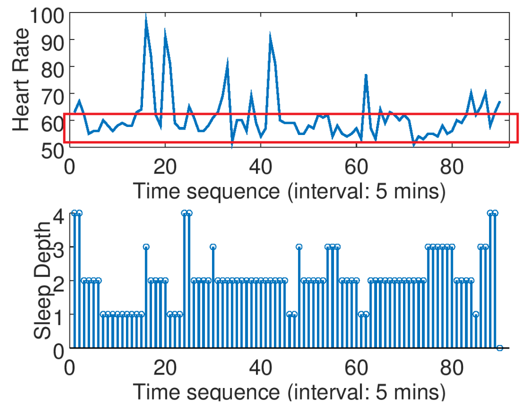


図 6 HRV and sleep depth on 18th June

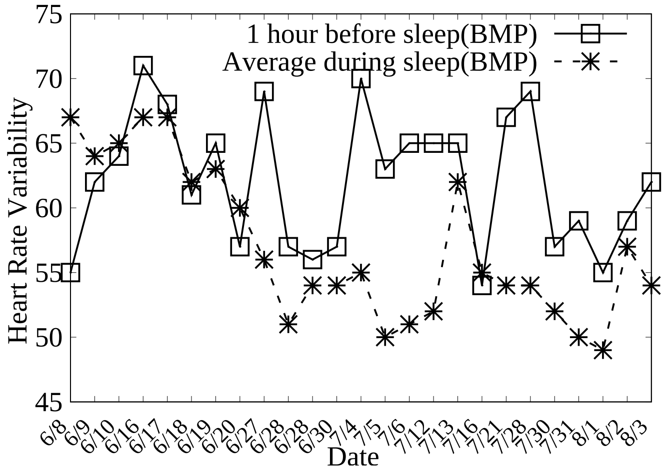


図 7 Comparison on HRV between 1 hour before sleep and average value during sleep

ever, according to Fig.4, there is seldom correlation in the trend of transition of *ratio* between RRI and sleep depth.

Figure 8 shows the result of stress index LF/HF. A comparison between RRI and sleep depth between 8th, June and 18th, June is plotted to show the difference between stressful and relaxing condition.

According to the both of periodgrams of RRI and sleep depth, more power spectral HF components on 18th than 8th with a more significant detectable peak value in HF component rather than in LF components, which make an inference that 18th data is relevant to a more relaxing sleep. More power spectral concentrated in LF components on 8th data and in PSD frequency component of sleep depth is difficult to detect due to a wide distribution of peak value points. Furthermore, LF/HF of sleep depth on 8th June is 3.23, which implies to a stressful condition, and the result is more convincing than that of RRI (LF/HF=0.69) according to the sleep depth and duration data listed in Table 2, Figs. 5 and 6. According to the result, LF/HF of sleep depth represented the stress condition more correctly than that of heart rate.

3.4 A discussion on correlation between heart rate and sleep depth during sleep

Many conventional works analyzed sleep quality and sleep depth by PSD of RRI, however, whether the LF/HF of RRI implies the sleep quality correctly and accordingly should be clarified. To achieve this, the correlation between heart rate and sleep depth is calculated and analyzed. Suppose sleep depth is $y(t)$ $(y, t \in \mathbb{R})$ in time sequence and i is the index of samples, then the correlation

表 3 Cross-correlation coefficients between HR and SD

6/8	**6/9**	**6/10**	**6/16**	**6/17**	**6/18**
0.078	-0.097	0.113	0.016	-0.162	-0.011
6/19	**6/20**	**6/21**	**8/4**	**Total**	
-0.461	-0.143	-0.467	-0.106	0.068	

表 4 Correlation coefficients between HR and SD (daytime v.s sleep)

	6/9	**6/16**	**6/17**	**6/19**	**6/20**
hr day v.s hr sleep	-0.047	0.042	0.090	0.190	-0.294
hr day v.s sd sleep	0.042	0.005	0.000	0.058	-0.185

coefficient

$$R = \frac{\sum_{i=1}^{t}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{t}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{t}(y_i - \overline{y})^2}} \qquad (7)$$

The result of correlation is listed in Table 3.

According to the results, there is correlation between heart rate and sleep depth on 6/19 and 6/21 and no correlation on the other days, either total data during this period. The reason is not clear since the conditions (light, temperature, etc) for experiment are similar.

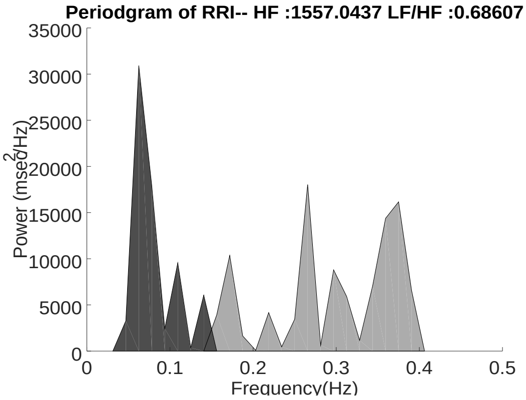
Kume et al. [10] identified a difference of autonomic nervous by comparing anxiety/relaxation indicator ΔLF/HF between listening to relaxing music and keeping silent, which is suggested to be related to the feeling of sleepiness and wakefulness for sleep quality. It also suggested that LF/HF might show a delayed response to fatigue.

Our experiment result of LF/HF on stress index on 8th and 18th, June is in consistency with the result in [10] that the participant was busying preparing a presentation on 8th for a group seminar to be held on 9th, Friday and feel stressful during daytime, while keeping relaxing on 18th, Sunday by attending a classical violin-piano concert during 13:00-16:00.

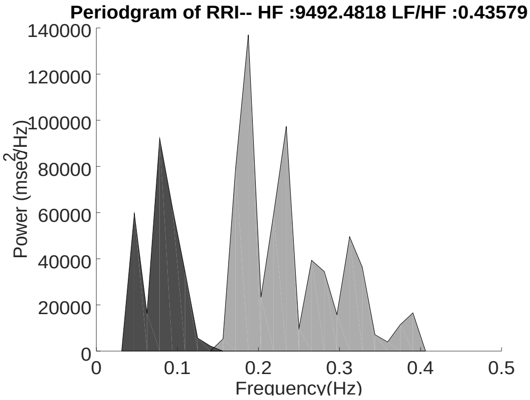
In order to clarify the effectiveness of daytime activities to sleep, we investigated the correlation of RRI during daytime v.s. RRI during sleep and RRI in daytime v.s. sleep depth during sleep adjusted to be with the same number of samples from the time stamp of falling asleep. The result is listed in Table 4. Seldom correlation are there between variables during daytime and sleep except data on 6/20 that heart rate during daytime has a low correlation to heart rate during sleep.

4. Discussion on privacy preserving

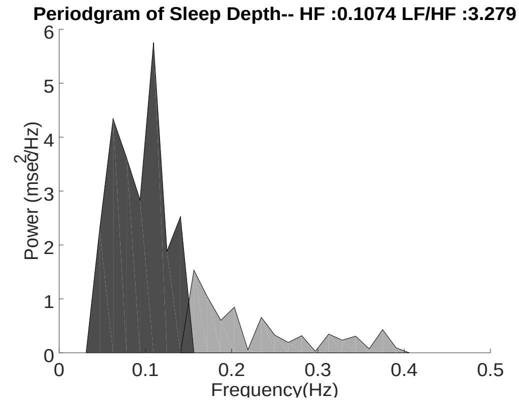
Disclosure of personal sensitive information to public is dangerous. A possible threat to plain data in the target application in Fig. 1 is that once the raw sensitive data of each providers are accessed by malicious attackers or



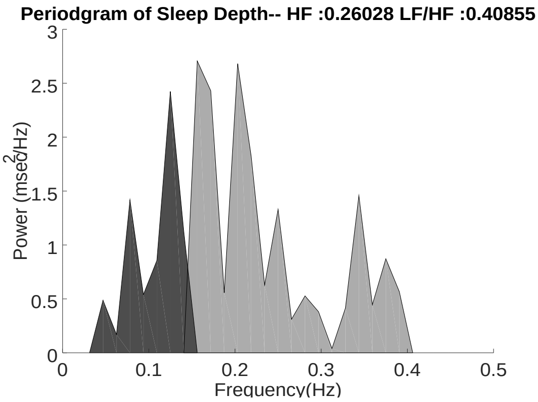
(a) Stress index LF/HF of RRI on 8th, June



(c) Stress index LF/HF of RRI on 18th, June



(b) Stress index LF/HF of sleep depth on 8th, June



(d) Stress index LF/HF of sleep depth on 18th, June

図 8 Comparison on stress index LF/HF of RRI and sleep depth on 8th and 18th June

表 5 Comparison on coefficients between proposed ad R (n=9)

	proposed	R			
variables	Estimate	Estimate	Std. Error	t value	$Pr(>\|t\|)$
α	84.034	86.098	6.214	13.855	8.8e-06
SD	-2.155	-3.024	1.608	-1.880	0.109
hours	-2.052	-1.081	1.130	-0.956	0.376

malicious insiders, the data may be used to identify the patient by combing other property information that the attackers have owned. Another possible threat is abuse of personal data without consent of the patient. Thus, guaranteeing and preserving the privacy of personal sensitive data have been important issues to consider.

With privacy preserving scheme applied to encrypted mHealthcare data, the following confidential analysis can be achieved: (1) identify correlation and effectiveness among different properties by linear regression; (2) predict sudden seizure of heart disease and disorder of sleep by analyzing regression of heart rate in frequency domain; and (3) send a value of certain mhealthcare property and return a disclosed risk indicator by privacy preserving data mining processing in clouds. In our work, we plan to apply a homomorphic cryptography algorithm to the sensitive data as $Enc(x(t))$ for further analysis.

We tried to apply privacy preserving linear regression, proposed by the coauthor [17] to calculate the multiple regression of $y = \alpha + \beta_1 x_1 + \beta_2 x_2$ with distributed data by independent two providers with Paillier encryption. Here, y is the heart rate, x_1 is sleep depth and x_2 is the overtime hours. The result is listed in Table. 5.

5. Conclusion

This work collected mHealthcare data including heart rate and sleep depth data during sleep via wearable IoT device with the purpose to analyze the stress conditions and sleep quality during sleep by spectral analysis on autonomic nervous stress index. We identified a stronger correlated between sleep quality and LF/HF of sleep depth rather than that of heart rate. Experimental results also suggest daytime activities affect sleep quality, however, the heart rate has seldom correlation to sleep depth.

Applying homomorphic cryptography to data analysis such as autocorrelation, spectral power density analysis for distributed data is listed as a future work. Improving sleep quality by analyzing the affective aspects such as environment data collected by IoT sensors and daytime activities with more sophisticated data and algorithm is another point we will focus on in the future.

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