# For Children's Sleep Assessment: Can we obtain RR intervals (RRI) and RRI variation parameters close to Polygraph ECG using small wearable ECG measuring device?

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*Abstract*— **To validate the quality of ECG data measured with our small and light weight wearable measuring device, M-BIT, we compared RR intervals (RRI) and parameters representing RRI variation of two ECG data simultaneously measured with M-BIT and polygraph.**

## I. Introduction

Short sleep duration and poor sleep quality may negatively affect physical health, such as obesity, diabetes, cardiovascular diseases, and hypertension, and psychological health, such as anxiety symptoms, depressed mood, concentration, performance, behavior, emotional instability [1, 2]. A cohort study about the effect of longitudinal sleep duration patterns to the obesity has reported persistently that the short sleep duration (<10 h) during early childhood (from 2.5 to 6 years old (y.o.)) significantly increases the risk of excess weight or obesity at the age 6 y.o.[3]. A cross-sectional study of the relationship between short sleep duration and obesity-related variables of children (5-10 y.o.) reported that when compared with children reporting12-13 h of sleep per day, the adjusted odds ratio for childhood overweight/obesity was 1.42 for those having 10.5-11.5 h of sleep and 3.45 for those having 8-10 h of sleep [4].

Early childhood is a period of intense development and a critical time for acquiring healthy sleep habits, hence poor quality sleep at early childhood negatively affects their whole subsequent life. To elucidate young children's sleep behavior precisely, we had developed small and light weight ECG and Acceleration measuring device, M-BIT (size: 40×39×8mm, weight: 14g, measuring duration: 25 hours). Although, we had reported detailed sleep analysis results of a kindergarten's four years old children [5,6], or even a trial of estimating sleep stage from RR interval variation [7], we had not compared RR intervals derived from M-BIT ECG and polygraph ECG directly or parameters representing these RRIV, such as, coefficients of variation of RRI (CVRR), para-sympathetic and sympathetic nervous systems activity (PSNS, SNS), respiratory frequency (RFRE) and variation of RFRE (VRFRE). To obtain reliable autonomic nervous system's activity, quality of sleep, respiration behavior, we have to prepare reliable RR intervals (RRI).

To validate the quality of ECG data measured with our small and light weight wearable measuring device M-BIT, we compared RRI and parameters representing RRI variation of two ECG data simultaneously measured with M-BIT and polygraph.

## II. Measurements and analysis

### A. Subjects

The subjects were volunteer students of Hosei University and staff members of the Ota memorial sleep center. (Kawasaki, Kanagawa). Although we planned measurements of 11subjects initially, results of both polygraph and M-BIT were obtained from 8 subjects (male: 5, female: 3, age: 22.1 ± 1.9, BMI: 23.4 ± 3.4). We obtained written consents and confirmation of their participation by their free will after the measurements were explained in details.

### B. Polygraph

To identify the sleep stage, we measured EEG (C3, C4, O1, and O2), musculus-mentalis EMG, right and left ocular movement. Electrodes resistances of the EEG measurement were lowered to less than 10kΩ. ECG measured with II lead. Sampling frequency was 256Hz and used a low-path filter of 35Hz.

### C. M-BIT

M-BIT allows 25-hour measurement with sampling frequency of 128 Hz (ECG) and 1Hz (3-axe acceleration). Electrode placement for ECG measurements used by M-BIT involves a monitoring lead, which is similar to lead II. A body ground is unnecessary due to improvements in the electronic circuit design. M-BIT is small and light-weighted, allowing it to be adhered to a subject's thorax using two electrodes [5, 6].

### D. RR interval detection

We detected time locations of the R wave on the ECG signal based on well-known robust real time QRS detection algorithm [8]. In this algorithm, ECG row data's 5 to 11 Hz, a frequency band of most information about QRS peaks, of were extracted by way of a band pass filter. Then, they were differentiated, converted to absolute values and averaged with 80-millisecond's window. Thus, QRS peaks converted to a

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hill like waveforms, and the location of R wave is a point where the waveform exceeds a certain defined threshold level.

There were still two weak points above algorithm. The first point was that the obtained points did not correspond to peak points of the original ECG waveform. The second point was the existing assumption that the hills originated from T waves are always smaller than those from R waves. However, in the actual situation, we have met ECG data with smaller R wave and larger T wave many times.

For the first point, after detecting a candidate point, we checked the original ECG data, and searched the nearest R wave peak, for the second point, we used the difference of the sharpness between R wave and T wave.

The ECG signal areas in inferior quality due to body movement or deterioration of contact between the skin surface and electrode, or the superimposition of power line alternating-current noise, however, may generate a false RR interval (RRI) and affect the results of the RRIV analysis. We have been taking two different approaches for classifying false RRIs and removing them.

At first, we calculated the RRI duration distribution of all the RRIs, and removed isolated outliers of abnormally large or small durations. Then, we focused on RRIs with "jumped out" duration in successive RRIs for a period of tens of seconds.

### *E. Closeness of RR Intervals from Polygraph and M-BIT*

We evaluated the closeness of M-BIT ECG RRIs (MRR) to Polygraph ECG RRIs (PRR) by error ratio (ER) of MRR to PRR, ER=1-abs(PRR-MRR)/PRR, and calculated total ER (TER) and epoch ERs (EERs) . If there is no error, then these error ration is 1 by definition. Here, duration of our analyzing epoch is 1 minute.

### *F. RRI variation representing parameters*

In this study, we focused on three basic parameters, coefficients of variation of RRI (CVRR), para-sympathetic nervous systems activity (PSNS) and respiratory frequency (RFRE).

We calculated CVRR as epoch standard deviation of RRIs/ epoch average of RRIs.

Since high frequency (> 0.15Hz) variations of RRI are caused by the mechanism whereby the output of the para-sympathetic nervous system is intercepted during inspiration, and only works during expiration, higher frequencies of the RRI variation is the frequency of respiration. Novak et al. [9, 10] demonstrated that the time frequency MAPs of RRIV and respiration were remarkably similar to each other.

Jasson et al. [11] resampled the RRI time series using a re-sampling frequency of 2Hz, and performed a time frequency analysis up to 1Hz. They calculated instantaneous central frequencies of high/low and the entire frequency regions, and indicated that the instantaneous central frequency in the high frequency bands corresponds to the respiration frequency. On the other hand, Bailón et al. [12] proposed that a re-sampling frequency of 5Hz and frequency analysis up through the frequency of the average heart rate is necessary when considering respiration.

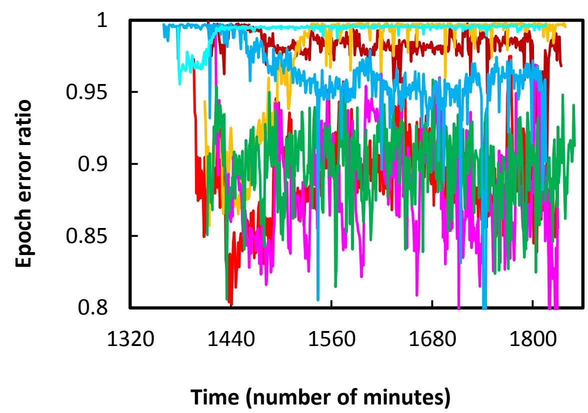


Fig.1 Epoch error ratios. (Red: st2, Brown: st3, Orange: st4, Magenta: st8, Green: st9, Blue: st10, Aqua: st11)

Based on Bailón et al. [12], we used a re-sampling frequency of 4Hz. Here, we assumed that 180bpm (3Hz) is the maximum daily heart rate of ordinal subjects. We performed time/frequency analysis of RRIV using the SPWV (Smoothed Pseudo Wigner-Ville) method with the highest available frequency resolution setting for each epoch [13], and obtained time/frequency MAPs (the results of time/frequency analysis).

Through extending the method of Jasson et al. [11], we calculated an instantaneous central frequency (CFR) from 0.15Hz to the half frequency of the average heart rate of each epoch. We defined the raw respiration frequency as a 10-second average of these CFRs, and obtained RFREas the average values of raw respiration frequency.

For PSNS, we calculated HF (high frequency components) as the sum of the absolutes of mapped values of corresponding frequency bands along the frequency axis and their average along the time over the map.

### *G. Closeness of RRI variation representing parameters (RRIVRP)*

We calculated epoch error ratio of RRIVRPs (EERRP) as EERRP=1 - abs(PRR epoch parameter value - MRR epoch parameter value)/ PRR epoch parameter value.

## III. RESULTS AND DISCUSSION

### *A. Closeness of RR intervals*

In TABLE I, TERs of each data are shown with numbers of pairs used each calculation. Here, we used only 7 polygraph ECGs which gave RR intervals from entire recorded time span.

ECG data pairs were divided two groups. St3 (TER=0.983), st4 (TER=0.973), st10 (0.961) and st11 (0.993) showed excellent closeness, while st2 (TER=0.890), st8 (TER=0.884) and st9 (TER=0.900) sowed less excellent results.

To observe error ratio situation more precisely, we calculated EERs and they are shown in Fig.1.

TABLE I Total Error ratio (n=7)

| Subject | Total Error ratio | Numbers of pairs |
|---|---|---|
| st2 | 0.890 | 27897 |
| st3 | 0.983 | 20485 |
| st4 | 0.973 | 20887 |
| st8 | 0.884 | 23177 |
| st9 | 0.900 | 26029 |
| st10 | 0.961 | 23553 |
| st11 | 0.993 | 30995 |

## B. *Closeness of RRIV parameters*

TABLE II Total error ratio

| Subject | CVRR | PSNS | RFRE |
|---|---|---|---|
| st2 | 0.962 | 0.915 | 0.977 |
| st3 | 0.892 | 0.611 | 0.969 |
| st4 | 0.972 | 0.954 | 0.992 |
| st8 | 0.972 | 0.922 | 0.981 |
| st9 | 0.816 | 0.582 | 0.949 |
| st10 | 0.910 | 0.902 | 0.983 |
| st11 | 0.976 | 0.916 | 0.985 |

Total error ratio of RRIV parameters are shown in Table II. All the data sowed excellent closeness for RFRE, and four data showed excellent closeness (>0.95), two data showed less excellent closeness (around 0.9) and one data showed fairly good results (around 0.8) for CVRR. On the contrary, only one data showed excellent closeness for PSNS, and two data showed low level closeness.

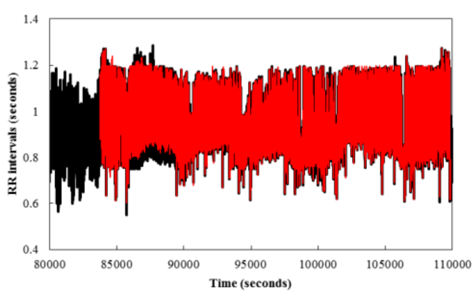


Fig.2 RR intervals of st2. (Red: Polygraph, Black: M-BIT)

It is interesting that in the case of st2 total error ratio for RRIs was 0.890, however, those for CVRR and RFRE were 0.962 and 0.977, and for PSNS was 0.915. As shown in Figs 1 and 2, in the case of st2 large difference were observed only in localized area. This may be the reason for above results.

On the contrary, in the case of st9, although there is no large difference zone, small difference scattered entire region. This may cause low closeness both in RR interval and RRIV parameters.

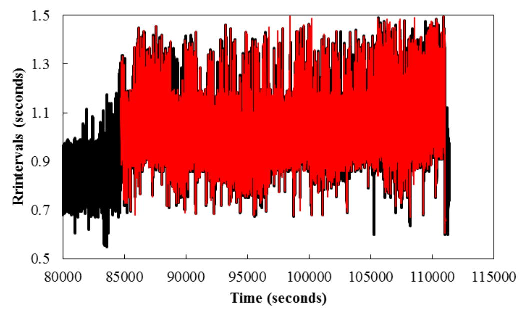


Fig.3 RR intervals of st9. (Red: Polygraph, Black: M-BIT)

## C. *Concluding remarks*

As an example of low closeness case, here, we considered PSNS of st9 together with its CVRR, as shown in Figs 4 and 5, respectively.

Although, there are many spike type difference, we put the hypothesis that even in multiple polygraph ECG simultaneous measurement, this level of error may occur, and we can use M-BIT ECG instead of Polygraph ECG. We are planning to perform multiple polygraph ECG simultaneous measurement.

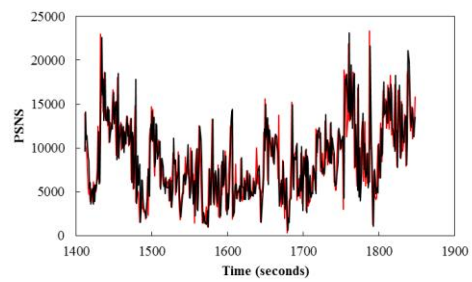


Fig.4 Epoch PSNSs of st9. (Red: Polygraph, Black: M-BIT)

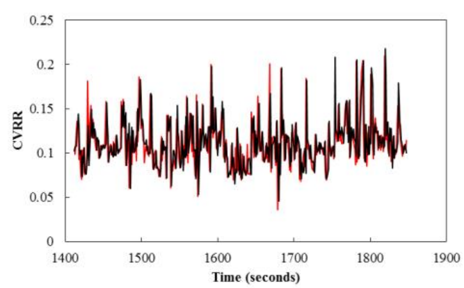


Fig.5 Epoch CVRRs of st9. (Red: Polygraph, Black: M-BIT)

## REFERENCES


[1] N. Michels, E. Clays, M. De Buyzere, B. Vanaelst et al., “Children's sleep and autonomic function: low sleep quality has an impact on heart rate variability,” *SLEEP,* vol. 36, pp. 1939-1946, No.12, 2013.

[2] Institute of Medicine (U.S.), “Extent and Health Consequences of Chronic Sleep Loss and Sleep Disorders,” Sleep Disorders and Sleep Deprivation: An Unmet Public Health Problem, in H. R.Colten, B. M. Altevogt Eds. Washington: National Academies Press, 2006, pp.55-135.

[3] E. Touchette, D.Petit D, R. E.Tremblay et al., “Associations between sleep duration patterns and overweight/obesity at age 6,” *SLEEP*, vol. 31, pp.1507-1514, No.11, 2008.

[4] J. P. Chaput, M. Brunet and A. Tremblay, “Relationship between short sleeping hours and childhood overweight/obesity: results from the ‘Que´bec en Forme’ Project,” *International Journal of Obesity*, vol.30, pp.1080–1085, 2060.

[5] S. Shirouzu, E. Shirouzu, Y. Seno et al., “Four Years Old Children’s Physical Activity: Can we confirm the difference of physical activity due to the difference of educational program?,” *2014 Health Innovations and Point-of-Care Technologies Conference*, pp.129-132, 2014.

[6] S. Shirouzu, E. Shirouzu, S. Fujitani et al., “Four Years Old Children’s Sleep: What can we obtain by using wearable measuring devices at their home?,” *2014 Health Innovations and Point-of-Care Technologies Conference,* pp.189-192, 2014.

[7] S. Shirouzu, Y. Seno, K. Tobioka et al., “For Children’s Sleep Assessment: Can we trace the change of sleep depth based on ECG data measured at their respective home with a wearable device?,” *2016 IEEE-EMBS International Conference on Biomedical and Health Informatics,* 2016.

[8] P. S. Hamilton and W. J. Tompkins, “Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmia database,” *IEEE Trans Biomed Eng.*, vol.33, pp.1157-1164,1986.

[9] P. Novak, V. Novak, J. de Champlain et al., “Influence of respiration on heart rate and blood pressure fluctuations,” *J Appl Physiol.*, vol.74, pp.617-626 1993.

[10] P. Novak, V. Novak, “Time/frequency mapping of the heart rate, blood pressure and respiratory signals,” *Med Biol Eng Comput.*, vol.31, pp.103-110 1993.

[11] S. Jasson, C. Medigue, P. Maison et al., “Instant Power Spectrum Analysis of Heart Rate Variability During Orthostatic Tilt Using a Time-/Frequency-Domain Method,” *Circulation*, vol.96, pp.3521-3526, 1997.

[12] R. Bailón, P. Laguna, L. Mainardi et al., “Analysis of Heart Rate Variability Using Time-Varying Frequency Bands Based on Respiratory Frequency,” *Proc. 29th Ann. IEEE EMBS Int. Conf.*, Lyon, France pp.6674–6677 2007.

[13] L. Cohen, “Time-Frequency Analysis,” Prentice-Hall Inc, New Jersey, 1995.