

# Supplementary Material

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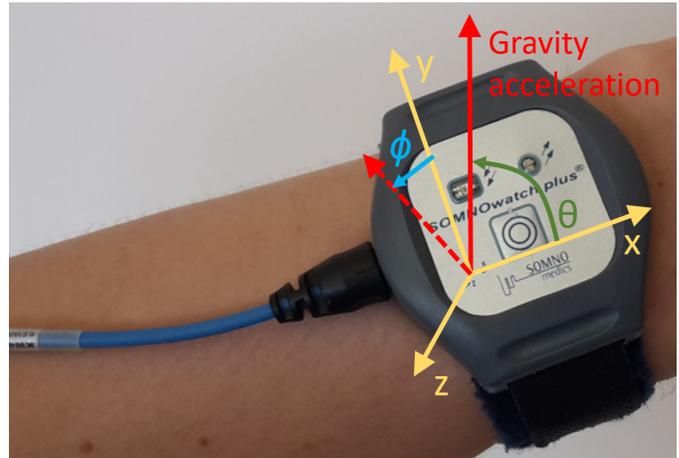
This online supplementary material for the paper Zschocke *et al.*, 'Reconstruction of Pulse Wave and Respiration from Wrist Accelerometer During Sleep', published in IEEE Transactions on Biomedical Engineering, 2021, contains additional information about our studies and describes some methods in more detail.

## SYNCHRONIZATION OF SOMNOWATCH™ AND PSG RECORDINGS

The figure shows a photo of the SOMNOWATCH™ device placed at the wrist of a subject. Since ECGs were recorded simultaneously by SOMNOWATCH™ and the PSG systems, these time series were used for establishing synchronization between the recording devices. As first step, the temporal positions of all R-peaks were determined using the package BioSPPy in Python [56] for the PSG data and LibRasch [57] for the SOMNOWATCH™ data. Then, starting 5 minutes after the lights-off time, for each segment of 20 minutes ECG data, the SOMNOWATCH™'s R-peak positions were linearly fitted to the PSG system's R-peak positions, yielding a time shift value (offset) and a drift value (slope) of the linear fit. For each segment, the fitting procedure was repeated 2401 times: for R-peak position time series shifted with respect to each other by  $-20$  minutes up to  $+20$  minutes with 1 second increment. Only the best fit was retained for each segment of 20 minutes ECG data, and the time shift used for that fit was added to the offset. Segments with less than 500 R peaks in 20 minutes for either SOMNOWATCH™ or PSG system were disregarded, assuming insufficient ECG signal quality. A visual inspection of the best time shifts (offsets) obtained this way for all 20-minutes segments was performed to check if any time gaps occurred in the PSG data throughout the night and if the time shift increased approximately linearly with the progressing night. Then the result for the segment with the smallest fitting error was used to correct time shift and drift for the whole night.

## COMPARISON OF GROUPS OF INCLUDED AND EXCLUDED SUBJECTS

Table II compares many clinical and sleep-related parameters for the group of 226 included data sets (subjects) and the group of 213 excluded data sets. As written in Subsection II.A, the procedure described in the previous section was unsuccessful for 105 subjects, and another 108 subjects had to be excluded because of noisy or corrupt respiration recordings. Only small differences in age ( $\Delta_{\text{age}} = 3.5$  y,  $p = 0.009$ ), total sleep time ( $\Delta_{\text{TST}} = 17.5$  min,  $p = 0.018$ ), and wake after



**Fig. 9. Acceleration and ECG recording at the wrist.** The photo shows the commercial medical device SOMNOWATCH™ plus (Somnomedics GmbH, Randersacker, Germany) placed at the wrist with the coordinate axes ( $x$ ,  $y$ , and  $z$ ; yellow) according to its orientation as well as the gravity acceleration vector (red) pointing vertically upwards from the center of the earth. The device measures the three components of the gravity acceleration with respect to its coordinate axes. From this data the two orientational angles,  $\theta$  = angle between  $x$  axis and gravity acceleration (see Eq. (4)) and  $\phi$  = angle between  $y$  axis and projection of the gravity acceleration into the  $y-z$  plane (dashed red vector) can be calculated (see Eq. (3)). In addition, the device records the ECG via the attached blue cable, using three electrodes. There is also a passive light sensor used to identify lights-off periods during the night and a LED indicating the recording period, but both are placed on the front of the device and therefore cannot be used to measure a photoplethysmogram.

sleep onset ( $\Delta_{\text{WASO}} = 12.9$  min,  $p = 0.015$ ) are significant. We found no significant differences regarding pathologies, smoking, alcohol consumption, and snoring habits.

**TABLE II**  
**COMPARISON OF INCLUDED AND EXCLUDED DATA SETS**

	included data	excluded data
male / female	117 / 109	109 / 100
Age [y]	48.6 $\pm$ 13.9	52.1 $\pm$ 13.8
Size [cm]	173.1 $\pm$ 10.1	173.2 $\pm$ 10.2
Weight [kg]	83.7 $\pm$ 18.8	85.5 $\pm$ 20.4
BMI [kg/m <sup>2</sup> ]	27.9 $\pm$ 5.7	28.4 $\pm$ 6.2
time in bed [min]	455.3 $\pm$ 46.3	452.0 $\pm$ 54.8
sleep onset latency [min]	18.4 $\pm$ 15.9	19.7 $\pm$ 20.2
total sleep time [min]	377.1 $\pm$ 72.3	359.6 $\pm$ 70.9
wake after sleep onset [min]	59.8 $\pm$ 49.1	72.7 $\pm$ 52.8
fraction of N1	0.204 $\pm$ 0.150	0.230 $\pm$ 0.149
fraction of N2	0.440 $\pm$ 0.123	0.428 $\pm$ 0.126
fraction of N3	0.186 $\pm$ 0.101	0.186 $\pm$ 0.112
fraction of REM	0.170 $\pm$ 0.081	0.157 $\pm$ 0.088
apnea hypopnea index [/h]	14.5 $\pm$ 18.7	16.6 $\pm$ 22.0
periodic limb movement ind. [/h]	13.8 $\pm$ 23.7	15.4 $\pm$ 27.4

## CALCULATION OF RECONSTRUCTED PULSE WAVE PHASES

In the following, we describe the data processing from the raw acceleration signal to the pulse wave phases, corresponding to the pulse wave peaks transversing the wrist. As already mentioned in II-C\*, the pulse wave information is hidden behind a high-frequency tissue vibration. Therefore we first apply a 5 to 14 Hz FFT bandpass filter on each raw acceleration axis separately (e. g., light blue curve in Fig. 1 (b)\*. for the  $y$  axis) and uncover the signal by the absolute of its Hilbert transform (red curve in Fig. 1 (b)\*). In order to extract only the main systolic pulse wave, we (i) subtract a moving average of 1.0 second window length and (ii) calculate a moving average over 0.43 seconds to obtain periodic signals, i.e., the pulse wave reconstructions  $A_x^{PW}$ ,  $A_y^{PW}$ , and  $A_z^{PW}$  (green curve in Fig. 1 (b)\*). We note that this procedure corresponds to another narrow band pass filter applied to the amplitude signal with a passband around 50 to 70 oscillations per minute, which correspond to the typical heart rate during sleep [58]. Both filter parameters, 1.0 second and 0.43 seconds, have been optimized for best phase synchronization of the pulse wave reconstructions with respect to the ECG-derived reference.

Pulse wave phases  $\varphi(t)$  have been calculated by applying another Hilbert transform to the pulse wave reconstructions and using the arctan2 function,

$$\varphi(t) = \arctan2(\Im(HT(A(t))), \Re(HT(A(t))), \quad (2)$$

where  $\Re$  denotes the real part and  $\Im$  the imaginary part of the Hilbert transform HT [39]\*. The procedure was applied to all pulse wave reconstructions  $A_x^{PW}$ ,  $A_y^{PW}$  and  $A_z^{PW}$ .

Furthermore, we derived rotation angles of the wrist from the pulse wave reconstructions,

$$\phi(t) = \arctan2(A_z^{PW}, A_y^{PW}) \quad (3)$$

$$\theta(t) = \arccos\left(\frac{A_x^{PW}}{\sqrt{(A_x^{PW})^2 + (A_y^{PW})^2 + (A_z^{PW})^2}}\right) \quad (4)$$

The acceleration axes  $y$  and  $z$  are orthogonal to the wrist, while the  $x$  axis is parallel to the lower arm. Therefore,  $\phi$  represents the rotation angle around the lower arm axis (roll angle), and  $\theta$  represents the turning angle with respect to the elbow (pitch angle).  $\phi(t)$  and  $\theta(t)$  are smoothed by a subtracting 1.0 second moving average and applying a moving average of 0.43 seconds. Finally, we applied Hilbert transform and calculated the corresponding phases  $\varphi_\phi^{PW}$  and  $\varphi_\theta^{PW}$  by arctan2, as described above in (2).

## CALCULATION OF RECONSTRUCTED RESPIRATION PHASES

Wrist acceleration data recorded during sleep contains not only pulse wave information but also respiration activity. To

derive respiration reconstructions and obtain a phase information  $\varphi^{RESP}$  from the raw acceleration signals, we followed six steps, separately for each axis:

- i) Apply a 1.0 second moving average. The window size of one second for the moving average was chosen such that there is typically one heartbeat in each window so that effects of heartbeats and pulse wave propagation through the wrist are systematically dampened.
- ii) Down sampling from 128 Hz to 4 Hz, since respiratory activity does not involve high-frequency components.
- iii) Calculate  $\phi$  and  $\theta$  according to (3) and (4).
- iv) Subtract a 10 seconds moving average, also for  $\phi$  and  $\theta$ .
- v) Divide by a 10 seconds moving standard deviation, also for  $\phi$  and  $\theta$ . This leads to the respiration reconstructions  $A_x^{RESP}$ ,  $A_y^{RESP}$ ,  $A_z^{RESP}$ ,  $A_\phi^{RESP}$ , and  $A_\theta^{RESP}$ .
- vi) Apply a Hilbert transform and arctan2 to calculate the respiration phases (see (2)).

A detailed explanation of this procedure can be found in [22]\*.

## REFERENCES

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- [57] R. Schneider *et al.*, “Librasch: a programming framework for signal handling,” in *Institute of Electrical and Electronics Engineers 2004 – Computers in Cardiology*, 2004, pp. 53–56.
- [58] S. Patra and S. Telles, “Heart rate variability during sleep following the practice of cyclic meditation and supine rest,” *Applied psychophysiology and biofeedback*, vol. 35, no. 2, pp. 135–140, 2010.

\*Referenced Section, Figure or Reference can be found in Zschocke *et al.* 2021