Continuous Monitoring of Sleep-Related Biomarkers via a Nearable Solution Based on Fiber Bragg Grating Technology

Supplementary Materials

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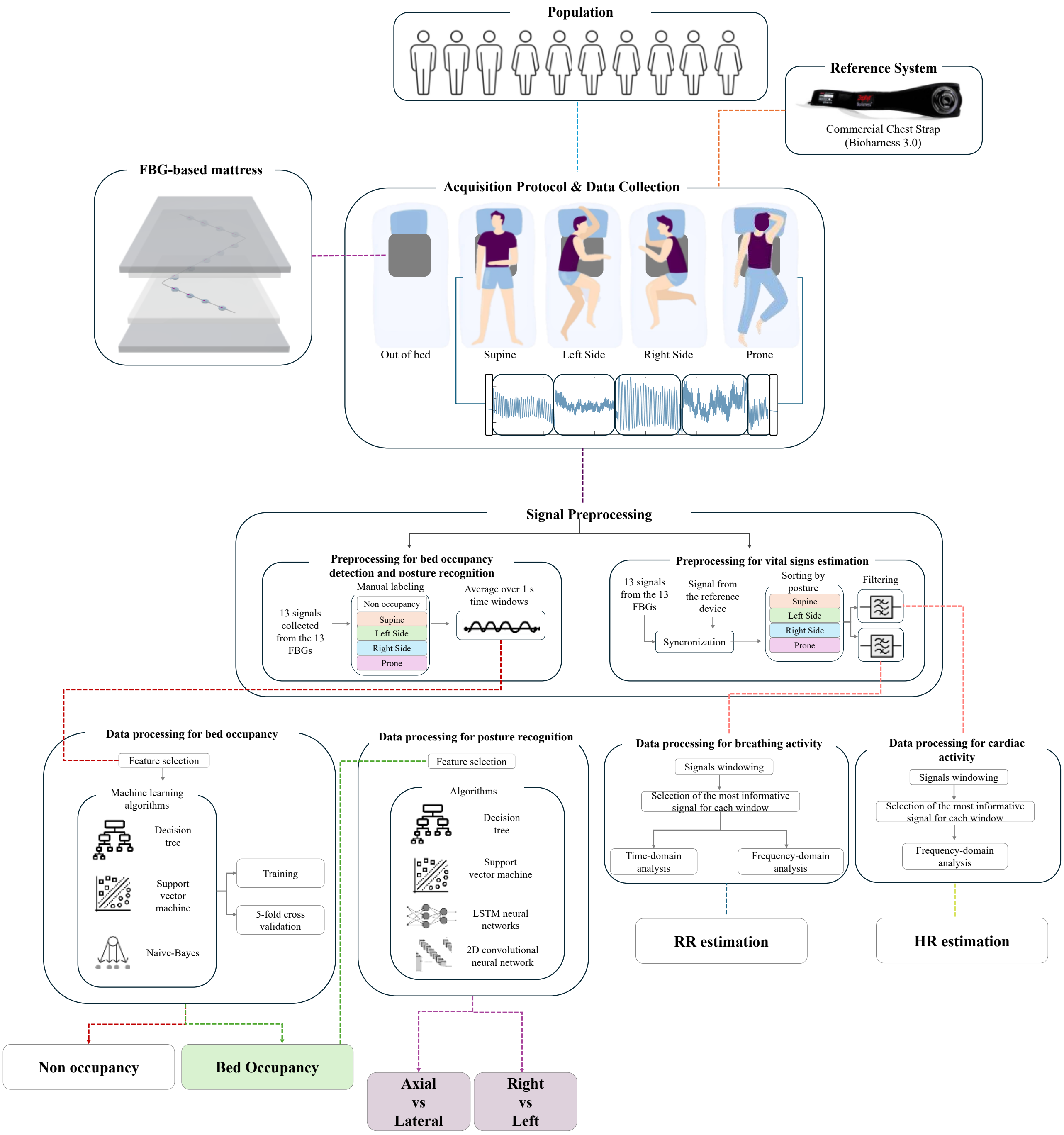

Figure S1. Flowchart summarizing the workflow of the FBG-based system from data acquisition to analysis and biomarkers estimation.

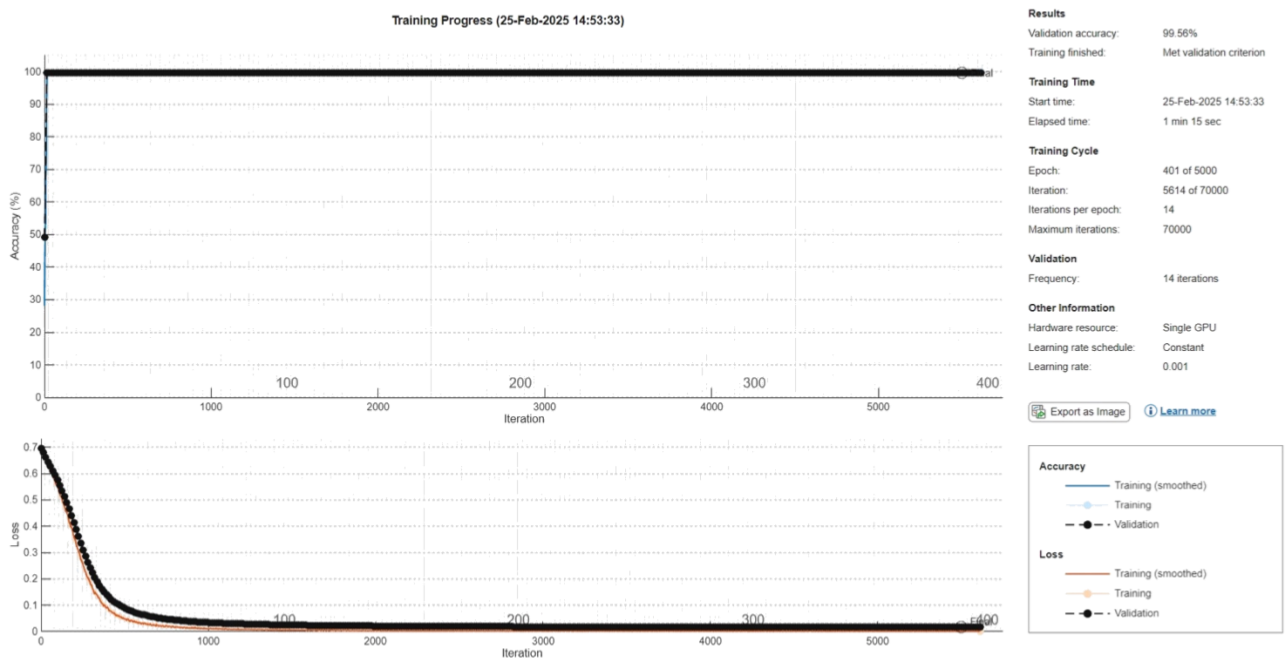

Figure S2. Example of a convergence curve of a Convolutional Neural Network for the discriminative task right vs left position, for Subject 1.

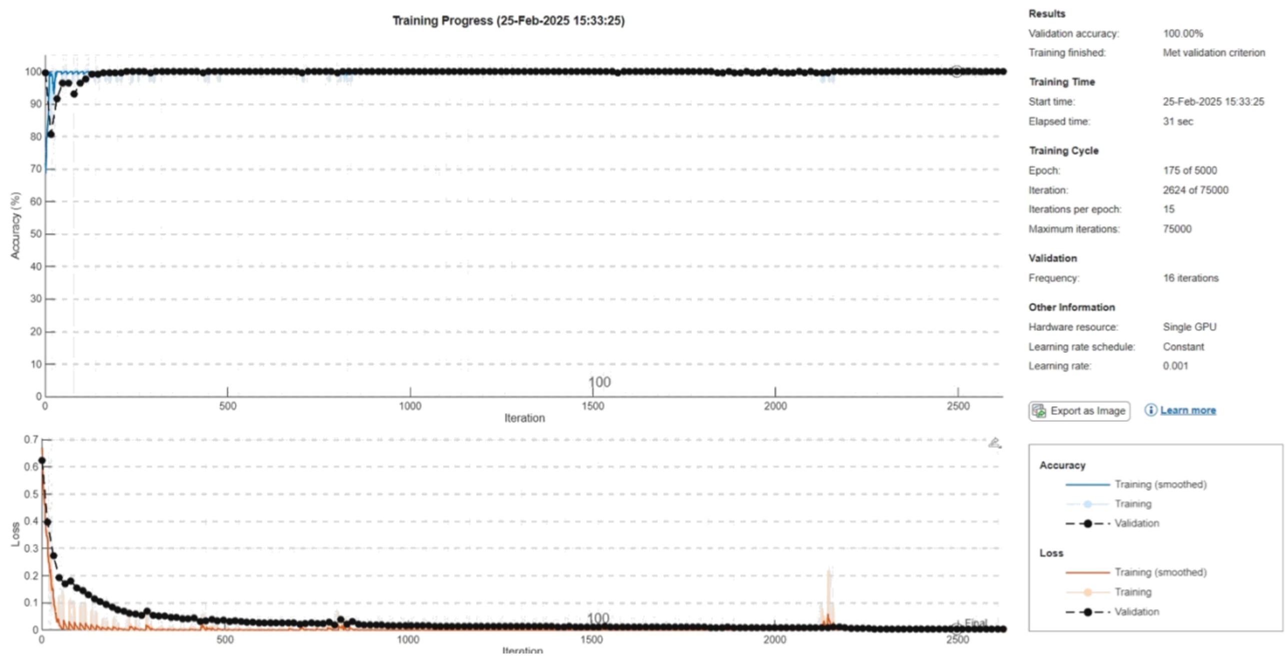

Figure S3. Example of a convergence curve of a Long Short-Term Memory Neural Network for the discriminative task axial vs lateral position, for Subject 1.

Table SI. Comparison with other similar existing sleep monitoring systems.

Reference	Sensing technology	Population, Acquisition Protocol	Extracted Biomarkers	Data analysis	Main Results
[1]	Piezoresistive sensors	7 participants 4 different sleeping postures (supine, left side, right side, and prone). Participants asked to voluntarily modulate the respiratory activity for at least 3 min.	1) RR 2) Sleeping postures	1) Frequency-domain analysis with windows length of 10 s 2) Two-layer, artificial neural network, KNN, SVM, Decision tree, Naïve-Bayes	1) Bland-Altman analysis (RR between 10 and 60 breaths/min): MOD±LOAs= 5.6±21.5 breaths /min 2) Higher accuracy on validation test of 89.9% (no information about other performance metrics)
[2]	Pressure sensors (PSM commercial device)	1 neonatal participant for 5 h and 54 min of acquisition time	RR	1) Time-domain analysis 2) Frequency domain analysis	1) MAE= 9.18 breaths/min 2) MAE=22.2 breaths/min
[3]	Microbend fiber optic sensor	10 participants Only supine position	1) RR 2) HR	Frequency-domain analysis	3) Bland-Altman analysis (RR between 6 and 30 breaths/min): MOD±LOAs= -0.1±5.05 breaths /min 4) Bland-Altman analysis (HR between 58 and 111 bpm): MOD±LOAs= -0.2±5.02 bpm
[4]	Ferroelectrect sensors (Emfit commercial device)	34 participants, with each volunteer contributing a maximum of 1 h of collected data (no details about posture)	1) RR 2) HR	HR and RR calculated from 1 min windows in every 4 s	5) Bland-Altman analysis (RR between 10 and 22 breaths/min): MOD±LOAs= -0.14±2.36 breaths /min 6) Bland-Altman analysis (HR between 40 and 82 bpm): MOD±LOAs= 0.03±4.4 bpm
[5]	Load cells	16 participants 6 different postures (supine, left and side, and 30°, 45°, 60° sitting postures). No details about acquisition time.	RR	Breath-by-breath analysis	1) Bland-Altman analysis (RR between 10 and 40 breaths/min): Supine: MOD±LOAs= 0.19±3.08 breaths/min Left side: MOD±LOAs= 0.21±2.85 breaths/min Right side: MOD±LOAs= 0.22±3.13 breaths/min
[6]	Fiber Bragg grating sensors	5 healthy participants 7 min for each sleeping postures (supine, prone,	RR	Frequency-domain analysis with RR computed every 30 s windows sliding every 1 s	Bland-Altman analysis (RR between 8 and 53 breaths/min): MOD±LOAs= 0.01±0.99 breaths /min

		left and right sides) mimicking only quiet breathing and tachypnea conditions			
[7]	Fiber Bragg grating sensors	8 healthy participants 10 min for each sleeping postures (supine, prone, and right side) mimicking only quiet breathing and tachypnea conditions	HR	Frequency-domain analysis with HR computed every 30 s windows sliding every 1 s	Bland-Altman analysis: MOD±LOAs= -0.30±3.6 bpm
[8]	Piezoresistive pressure sensors	12 healthy volunteers (2 females and 10 males) 5 min acquisition time for each simulated sleeping posture (supine, prone, left and right sides).	1) RR 2) Sleeping postures	Posture based Kalman filtering + RR computation. RR are calculated using 30 s windows without any overlap and updated every 30 s	Bland-Altman analysis (RR between 6 and 23 breaths/min): Worst results in supine posture: MOD±LOAs= 0.35±2.11 breaths/min. Better results in prone position: MOD±LOAs= 0.08±1.38 breaths/min
[9]	Plastic optical fiber	10 participants (7 males and 3 females) 4 different behavioral states (not in bed, moving and leaving the bed) and 5 min acquisition time for each state For RR and HR estimation only 90 s acquisition time in supine position	1) RR 2) HR 3) Sleep behavioral states	1) Frequency-domain analysis with 30 s windows 2) Frequency-domain analysis with 30 s windows 3) Behavioral states classified according to the energy of the power spectral density	1) Absolute error up to 1.9 breaths/min 2) Absolute error up to 3.4 bpm 3) Order of magnitude different for each state (without classification algorithm)
[10]	Pneumatic sensors	24 participants (mostly composed of males) No details about acquisition time and position.	1) RR 2) HR	Time-domain analysis for both RR and HR.	1) Bland-Altman analysis (RR between 12 and 23 breaths/min): MOD±LOAs= -0.06±0.55 breaths/min (30.4% of data excluded by the algorithm) 2) Bland-Altman analysis (HR between 50 and 85 bpm): MOD±LOAs= -0.8±3.6 bpm (360% of data excluded by the algorithm)

[11]	Load cells	54 adults (excluding anyone unable to give informed consent and anyone unable to sit and stand up on their own without assistance) Acquisition protocol consisting of mimicking different positions (supine, right side, left side, prone, sitting in the center of the bed, on the right side and on the left side for a total of 200 s per each subject) and movements	1) Positions 2) Movements	Decision tree model	1) Accuracy: Supine/prone:75.9% Left side= 66.7% Right side=64.8% 2) Movements: Average accuracy of 79.7%
Present study	Fiber Bragg grating sensors	10 healthy participants (3 males and 7 females) 10 min for each simulated sleeping posture (supine, left side, right side, prone) mimicking different breathing patterns in terms of amplitude and frequency for a total acquisition time of 800 min	1)Bed occupancy 2) Sleeping posture 3) RR 4) HR	1) Bed occupancy classification through decision tree, SVM and Naïve-Bayes models 2) Classification between axial vs lateral positions and right vs left positions through CNN, LSTM, SVM, and decision tree 3)Reconstruction of the most informative signal. Frequency-domain analysis with RR computed using 30 s windows sliding every 1 s. Time-domain analysis with RR computed using 30 s windows. 4) Reconstruction of the most informative SCG signal. Frequency-domain analysis with HR computed using 30 s windows sliding every 1 s.	1) 100% accuracy 2) SVM achieved the highest accuracy of 78.4% in distinguishing between axial and lateral positions, while the CNN achieved the highest accuracy of 75.9% in distinguishing between left and right postures 3) Best results for frequency-domain analysis: • MAPE is less than 3% for 70% of the values. • Bland-Altman analysis (RR between 5-55 breaths/min): MOD±LOAs= -0.01±4.97 breaths/min (considering all the postures and breathing conditions) 4) Bland-Altman analysis (HR between 48-93 bpm): MOD±LOAs= -0.44±11.1 bpm (considering all the postures and breathing conditions)

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