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Mechano-acoustic sensing of physiological processes and body motions via a soft wireless device placed at the suprasternal notch

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Skin-mounted soft electronics that incorporate high-bandwidth triaxial accelerometers can capture broad classes of physiologically relevant information, including mechano-acoustic signatures of underlying body processes (such as those measured by a stethoscope) and precision kinematics of core-body motions. Here, we describe a wireless device designed to be conformally placed on the suprasternal notch for the continuous measurement of mechano-acoustic signals, from subtle vibrations of the skin at accelerations of around 10^{-3} m s^{-2} to large motions of the entire body at about 10 m s^{-2}, and at frequencies up to around 800 Hz. Because the measurements are a complex superposition of signals that arise from locomotion, body orientation, swallowing, respiration, cardiac activity, vocal-fold vibrations and other sources, we exploited frequency-domain analysis and machine learning to obtain—from human subjects during natural daily activities and exercise—real-time recordings of heart rate, respiration rate, energy intensity and other essential vital signs, as well as talking time and cadence, swallow counts and patterns, and other unconventional biomarkers. We also used the device in sleep laboratories and validated the measurements using polysomnography.

Natural processes of the human body yield a multitude of mechano-acoustic (MA) signals, many of which strongly attenuate at the skin–air interface[1–5]. Motions with amplitudes and frequencies ranging from subtle vibrations to full-body kinematics contain diverse and important physiological health information. Examples include vocal-fold vibrations (about 100 Hz), cardiac activity (about 10 Hz), gait and locomotion (about 1 Hz), respiration (about 0.1 Hz) and body orientation (about 0 Hz). Digital stethoscopes and inertial measurement units represent clinical-grade tools that quantitatively capture some of these and other MA data[6–9]. Digital stethoscopes acquire signals typically confined to a frequency range of 20 to 1,900 Hz, non-continuously and episodically[8].

Traditional inertial measurement units can be used continuously, but they are most effective at low frequencies (0–100 Hz) due mainly to their high inertial mass and loose coupling to the body[9,10]. These types of sensors cannot capture both mechanical and acoustic aspects of MA signals simultaneously with high fidelity. Compact, skin-mounted accelerometers and/or gyroscopes based on microelectromechanical systems offer important capabilities in this context, with demonstrated examples of capturing signatures of cardiac mechanics, such as seismocardiograms or ballistocardiograms[11–14], respiratory rate and sounds[15–21], sounds of swallowing[22–25], vocals[26,27], changes in body position and motion[28–30] and others[31]. Some of these measurements have direct relevance to medical applications,

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particularly when implemented in devices that monitor multiple physiological signals[1,3,32].

Conventional wearable devices for such purposes couple to the body in the form of straps, adhesive patches or bands, with the chest or wrist serving as the measurement interface[33–35]. Other body locations can be used, but there are substantial practical limitations that follow from the rigid, planar form factors of the devices[26,36,37]. For example, microphones strapped to the neck can capture acoustic signals associated with speech and throat sounds for detection of dietary behaviour and respiratory physiology[38], and accelerometers attached to the skin of the neck with wax can record a range of body processes for tracking patterns of sleep[36]. These types of systems cannot, however, support persistent, comfortable interfaces with the skin during normal daily activities. Soft, lightweight skin-compatible wireless devices with the ability to be mounted on unusual parts of the body can continuously track a full spectrum of mechanical and acoustic signatures of body processes. Potential applications include monitoring health status and social interactions throughout the day, quantifying sleep behaviours, measuring athletic performance and guiding rehabilitation protocols.

Recent advances in soft electronics[1,39–43] serve as the foundation for skin-compliant, lightweight devices that incorporate accelerometers based on microelectromechanical systems technologies[1]. The device in this study comprises a collection of functional components, encapsulated and supported by an elastomer and interconnected with serpentine conductive traces that maximize the measurement sensitivity by mechanically decoupling the sensing element from the supporting electronics[1]. The resulting 'epidermal' MA sensors are highly responsive to movements and vibratory processes of the body, with the ability to capture high-quality signals across frequencies from 0 Hz to the audible band, with minimal interference from ambient noise[1].

The advances presented here build on these initial findings through (1) the design of wireless systems optimized for a comfortable skin interface and high precision, high-bandwidth MA measurements, powered with small-scale rechargeable batteries; (2) the use of the suprasternal notch (SN) as a unique anatomical mounting location that offers a rich blend of MA information related to diverse classes of physiological processes and core-body motions; (3) the development of data analysis techniques for extracting quantitative physiological insights from the resulting multimodal data; (4) the combined demonstration of the unusual mechanics of the device, unique mounting locations and advanced analytic approaches in continuous or semi-continuous monitoring during routine daily activities and physical exercise; and (5) the clinical validation of results captured in sleep laboratories through quantitative comparisons to recordings obtained by gold-standard polysomnography systems.

Results

Engineering mechanics of the device. The thin, soft form factors of the system introduced here enable skin-interfaced measurements of MA signals continuously and wirelessly at nearly any location on the body, including sensitive regions such as the SN. High data fidelity and comfortable, non-irritating interfaces are key features. Figure 1a,b outlines the overall device layout, with images that demonstrate its ability to deform naturally with movements of the neck when mounted on the SN. The design incorporates deformable, non-coplanar serpentine interconnects, a strain-isolation layer at the base, a soft-encapsulation overlayer and a hollow air-pocket configuration. Together, these features provide low-modulus, elastic mechanics despite the incorporation of conventional rigid electronic components and flexible printed circuit board technologies with layouts that are compatible with high-volume manufacturing.

Figure 1b presents, more specifically, the overall structure of the system. The device consists of a flexible printed circuit board (fPCB) based on a 25-µm-thick middle polyimide support layer with patterned traces of 12-µm-thick rolled, annealed copper (Cu) on the top and bottom surfaces (AP7164R, DuPont), each encapsulated with an insulating layer of polyimide (25 µm, FR1510, DuPont)[44]. The main electronic subsystems include (1) a three-axis digital accelerometer (BMI160, Bosch) for measuring motions with a sampling frequency and resolution of 1,600 Hz and 16 bits, respectively, a broad bandwidth response (0–1,600 Hz) and a sufficient dynamic range ($\pm 2g$) (where g is the gravitational acceleration, 9.8 m s^{-2}); (2) a microcontroller (nRF52832, Nordic Semiconductor) for acquiring data from the accelerometer and communicating the results wirelessly via Bluetooth low-energy protocols; and (3) a wireless inductive charging circuit to support a rechargeable 45 mAh lithium-ion polymer battery (Fig. 1c).

Because these subsystems rely exclusively on rigid, planar off-the-shelf components, they must be carefully integrated in a manner that simultaneously offers soft, skin-compatible mechanics as well as effective mechanical coupling of the accelerometer to the body. The schemes used here exploit advanced versions of design concepts in stretchable electronics[43], adapted for use with the fPCB generally, and for the interconnects between the subsystems specifically. As shown in Fig. 1b, serpentine-shaped interconnects mechanically and electrically join two rectangular regions of the fPCB (islands; 1 cm × 1 cm). One island supports the microcontroller and charging circuit. Here, the fPCB folds onto itself to minimize the area taken up by the rigid components (Fig. 1b). The other island includes the charging coil and connections to the battery. The coil includes two Cu traces (120 µm wide) in a rectangular spiral design (8 turns, 100 µm pitch) on both top and bottom sides of the fPCB. This minimizes the overall size of the device while allowing larger electromagnetic flux to go through the coil compared with a single layer coil with the same dimension. The top and bottom coils share the same polarity and dimensions (9.55 mm × 10.7 mm). Electroplating (Contac S4) creates a conductive path across the two sides of the fPCB through holes located at the ends of the coils.

Small pieces of rigid printed circuit board material (Garolite G-10/FR4; 381 µm thick, 22 GPa modulus, McMaster Carr 1331T37) support each of the two main islands to increase their bending stiffness by three orders of magnitude (49 µm thick, 4.8 GPa modulus). This design effectively eliminates bending in these regions, thereby enhancing the robustness of the solder bonding joints between the components and the fPCB. These islands comprise 30% of the overall area of the system, leaving ~70% for freely deformable regions, including the serpentine-interconnect structures.

The accelerometer rests on a cantilever that extends from the component island via a thin, narrow region of the fPCB to allow effective coupling to the skin with minimal mechanical constraints from other parts of the system (dashed red outline in Fig. 1b). To prevent entanglement, the interconnects consist of two layers of serpentine wires embedded in silicone gel (Silbione 4717 Gel A/B, Elkem; 0.4 mm thick) with a low Young's modulus (6 kPa) to minimize constraints on deformation of the serpentine wires (Supplementary Fig. 1a). A pre-buckled, out-of-plane, arc-shaped geometry allows the serpentine interconnects to assume traction-free architectures that absorb tensile deformations in two distinct modes (Supplementary Figs. 1d, middle, and 2) in a manner largely decoupled from the bottom substrate of the device. Finite element analysis highlights significant mechanical advantages of these non-coplanar interconnects compared with conventional planar serpentine layouts (Supplementary Fig. 1 and Supplementary Note 2). At the optimized arc angle $\theta = 270°$ and with pre-buckling, the elastic stretchability, $\varepsilon = (L_y - L^*)/L^*$ (where L^* is initial length (Fig. 1d, left) and L_y is the length at which the Cu layer reaches the elastic limit) increases to 43% from 14% stretchability with arc angle $\theta = 210°$ and without pre-buckling (Fig. 1d, middle and Supplementary Fig 1b). Additional finite element analysis results

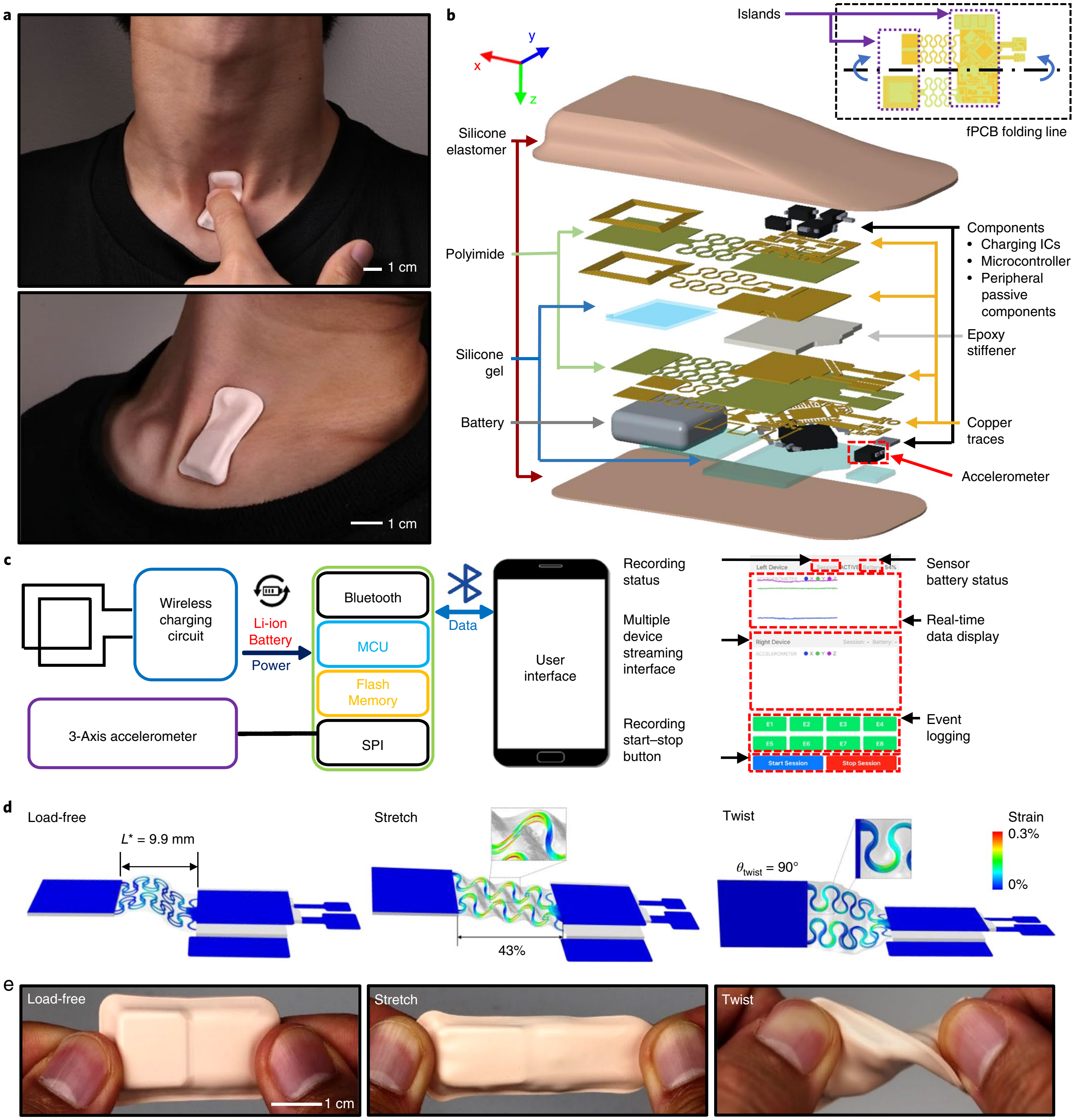

Fig. 1 | A wireless, skin-interfaced MA measurement technology designed for mounting on the SN. a, Images that demonstrate soft-device mechanics during movements of the neck while interfaced to the SN. **b**, Exploded schematic illustration of the active components, interconnect schemes and enclosure architectures. IC, integrated circuit. **c**, Block diagram of the system operation (Supplementary Note 1). **d**, Finite element modelling of the mechanics during uniaxial tensile and twisting deformations. **e**, Images of the device in undeformed (left), stretched (middle) and twisted (right) configurations.

indicate that the maximum effective strain in the Cu layer is significantly less than the yield strain (0.3%) under various mechanical loads (Fig. 1d, right and Supplementary Fig. 3). These results highlight the range of robust, low-modulus, elastic responses (Supplementary Figs. 4 and 5) necessary to accommodate realistic physiological motions with little constraint on the underlying skin (Fig. 1e). Supplementary Fig. 5 also shows that the fPCB thickness has little effect on the overall device modulus and stiffness. In addition to the mechanical characterization of the complete device, Supplementary Figs. 6–8 illustrate the effect of the packaging materials and device structure on the signal fidelity. Supplementary Fig. 6 compares z-axis acceleration recordings across a frequency range of 0 to 800 Hz, measured by a complete wireless system and by a wired, isolated accelerometer. The ratio between the two measurements is close to unity across the measurement range, demonstrating that the effects of the packaging materials are negligible. As shown

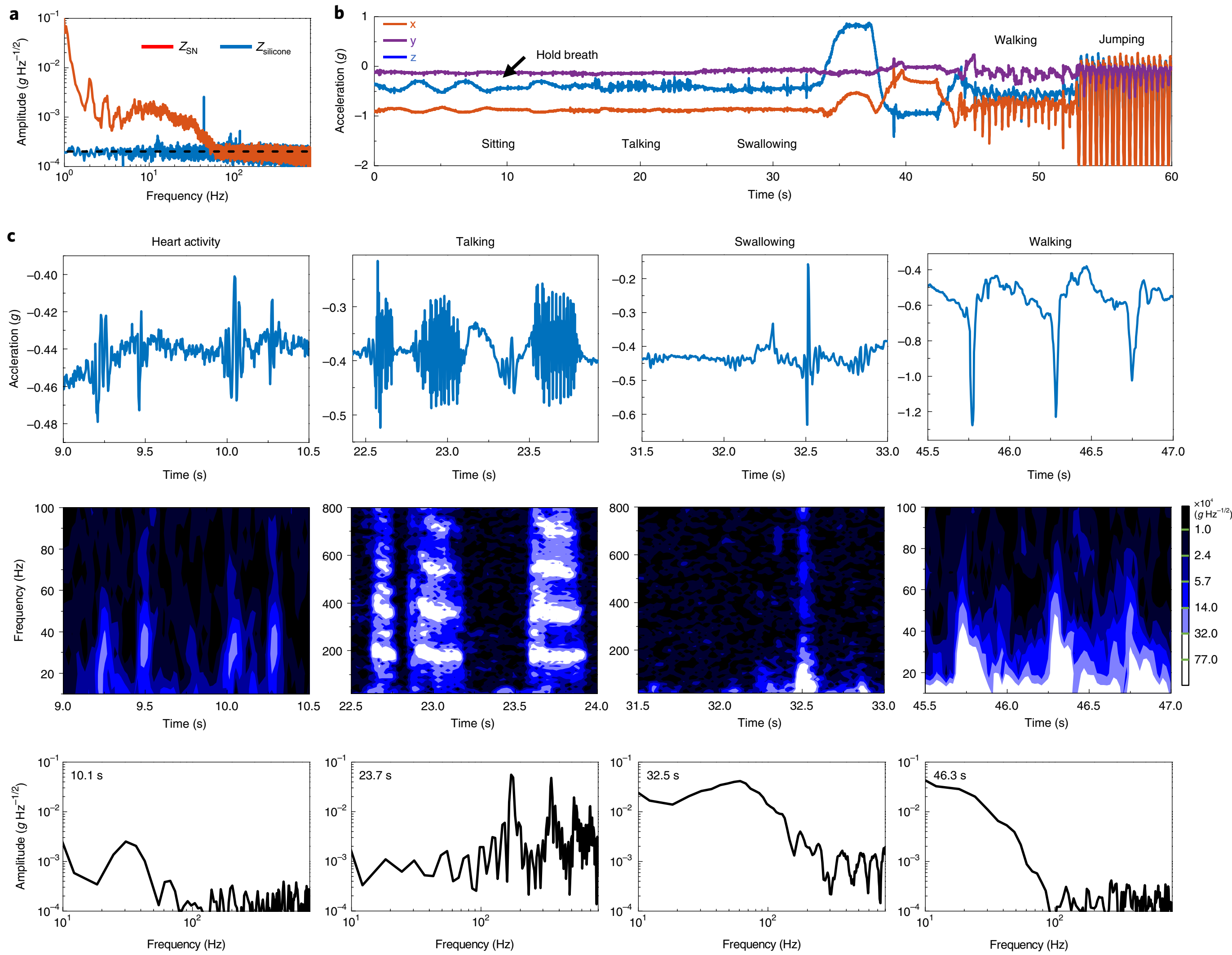

Fig. 2 | Representative MA data in the form of accelerations measured along three orthogonal axes from the MA device mounted on the SN of a healthy subject. a, Power spectral analysis of data (z-axis acceleration) collected from a device vertically resting on an elastomer (Z_silicone) and interfaced to the SN of a subject sitting quietly (Z_sn). The power spectrum of the measurement from the SN shows high power below 100 Hz associated with various involuntary physiological events. **b**, Three-axis time series data simultaneously recorded over a 60 s interval as a subject engages in various activities that include sitting at rest, talking, drinking water, changing body orientation, walking and jumping. **c**, Sample time-series data, spectrograms and spectral information corresponding to cardiac activity, talking, swallowing and walking. The colours indicate the amplitude spectral density. The frequency analysis uses a Hanning window with a width of 0.1 s moving in time steps of 0.02 s.

in Supplementary Figs. 7 and 8, results from a simple simulation model confirm these findings.

Data and analysis approaches for measurements from the SN. Natural physiological processes generate diverse MA signals at the surface of the skin, from subtle vibrations on the order of $\sim 1\times10^{-4} g\,\mathrm{Hz}^{-1/2}$ (Fig. 2a) to large-scale motions with amplitudes of $\sim 2g$, across a band of frequencies (0 to 800 Hz) that can be captured with the accelerometers used here. The SN represents a unique anatomical location for recording such signals, as a direct soft-tissue MA interface to vital organs related to cardiovascular, respiratory and digestive systems and their interconnections between the head and torso. Figure 2a shows the typical sensitivity of the device (along the z axis, axes defined in Fig. 1b) characterized when placed on a vertical slab of elastomer (4 mm thick, 60 kPa) and when interfaced with the SN (Fig. 1a) of a subject while sitting quietly. The sensor on the slab shows nearly uniform noise power density across the entire frequency range.

At the SN, proximity to the carotid artery results in vibratory signatures related to the pulsatile flow of blood. The periodic nature of these signals allows determination of heart rate and variability. The cross-correlation of pulses measured from the chest near the pulmonic area and the SN defines a time lag between these two signals (Supplementary Fig. 9). The lag of ~13 ms is consistent with recordings of vibratory signatures from the carotid artery itself, as opposed to chest–body vibrations. The amplitudes yield information on the intensity of cardiac activity and, indirectly, stroke volume. Passage of air through the trachea and movements of the chest wall produce MA data related to swallowing, talking, breathing, coughing, sighing, snoring and other responses. Furthermore, the device simultaneously responds to chest-wall and full-body movements, including orientation referenced to the gravity vector.

All such signals rise well above the noise floor of the measurement system. To demonstrate the collective capabilities, Fig. 2b presents representative three-axis acceleration data recorded from the SN of a healthy subject engaged in a sequential series of activities.

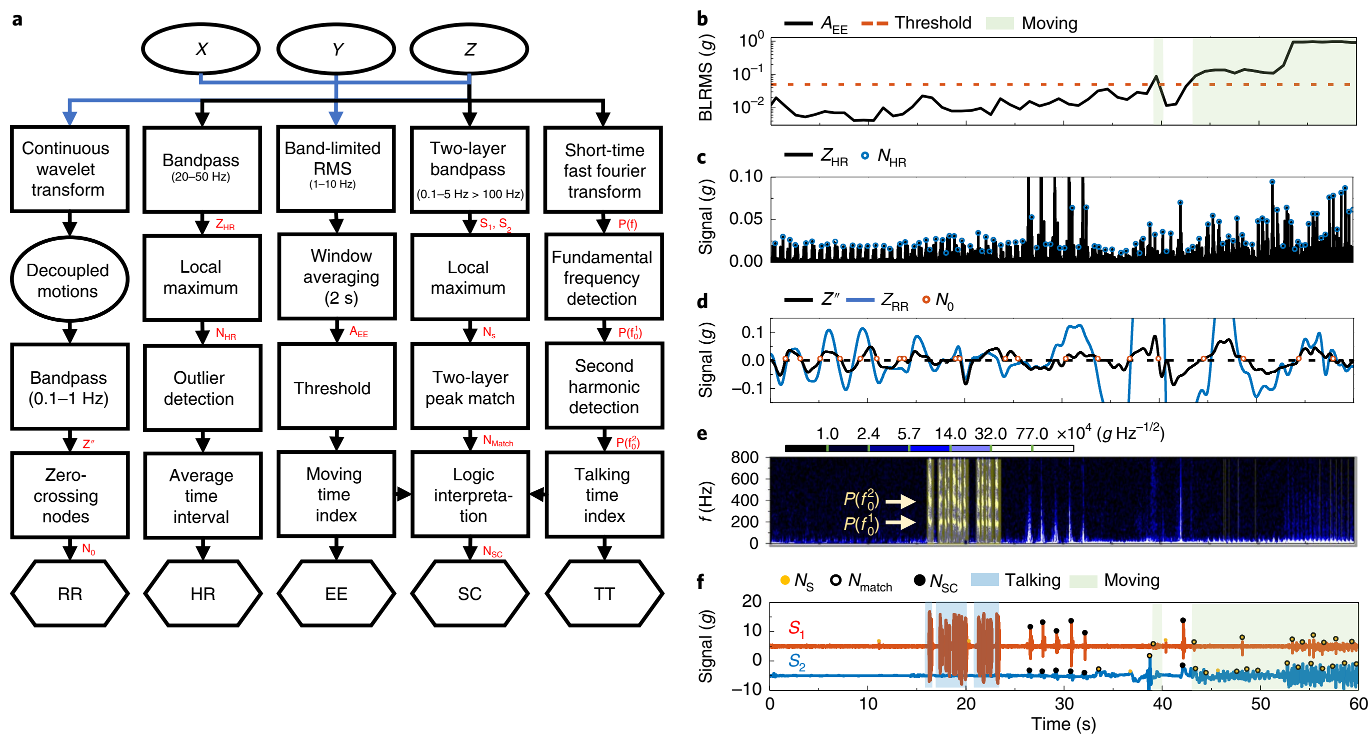

Fig. 3 | Flow diagram of signal processing and corresponding results from representative MA data acquired from healthy subjects. a, Block diagram of post-processing analytics for EE, HR, RR, SC and TT; blue arrows indicate use of three-axis accelerometer data and black arrows indicate use of *z*-axis data. EE, the window-averaged 1–10 Hz BLRMS sum of data from all three axes (A_{EE}) indicates the intensity of activities. For HR, detection of heartbeat peaks relies on identification of local maxima (N_{HR}) in 20–50 Hz band-passed waveforms (Z_{HR}). For RR, zero-crossing nodes (N_0) of the decoupled, 0.1–1 Hz band-passed chest wall motion (Z'') from three-axis measurements serve as the basis for RR estimation (Supplementary Note 3). For TT, the talking signals feature pronounced harmonics ($P(f_0^1)$ and $P(f_0^2)$) of fundamental frequencies (f_0^1) in the spectrogram analysis ($P(f)$). For SC, the broadband swallow-like events (N_{match}) correspond to occurrences of peaks (N_s) in both low-passed and high-passed signals (S_1 = 0.1–5 Hz; S_2 > 100 Hz). The algorithm outputs swallow-event N_{SC} that do not overlap with talking or activity periods. **b**–**f**, Application of the signal processing flow to the representative MA data (Fig. 2) for EE (**b**), HR (**c**), RR (**d**), TT and the colours indicating the amplitude spectral density (**e**) and SC (**f**) analysis.

The signals associated with each of these and other activities exhibit distinct features in time and frequency, thereby conveying a rich set of information related to body processes. The following analysis focuses, for simplicity, on accelerations measured along the direction normal to the surface of the skin (*z* axis).

The first 10 s of the data feature signals that arise from respiration. Here, expansion and contraction of the chest wall induce periodic rotations of the device around the *y* axis at the neck, along with some translational motions. The main effect is to change the magnitude of the projection of gravity along the *z* and *x* axes. Mounted on the SN, the device includes grounded points (for example, trachea) that do not move with the chest wall. Thus, the angular range of rotations (~1.3°) from respiration is larger than that associated with chest-wall movement alone (~0.5°). As the subject begins to hold his breath at the ~10 s mark, these periodic changes cease. Talking and swallowing generate high-frequency signals associated with acoustic vibrations and rapid motions, as shown in the data from 16–34 s. When the subject leans in different directions from 34–45 s, quasi-static 3D accelerations provide instantaneous measurements relative to the gravity vector indicative of body orientation. Walking (45–53 s) and jumping (53–60 s) induce large amplitude accelerations with significant projections along all axes.

Figure 2c shows quantitative details of the high-frequency features (>10 Hz) of individual physiological events. Cardiac activities—both systolic and diastolic[10]—give rise to paired pulses with peak amplitudes of ~0.05*g*, and power concentrated in a frequency band of 20–50 Hz. The speech signals feature high-quality harmonic structures with fundamental frequencies in the range of 85 to 255 Hz for typical adults[45,46]. Swallowing events initiate with slow motion (~0.1 s) of the vocal folds and with larynx mechanics during the pharyngeal phase and end with a high-frequency ring-down associated with flow of water or food during the oesophageal stage[6]. Large impact forces that span broad frequency ranges up to ~100 Hz characterize walking motions.

The characteristic frequencies and temporal structures of these features do not depend critically on the subject (gender, body type, ethnicity and age) (Supplementary Fig. 10) or the mounting location in the vicinity of the SN (Supplementary Fig. 11), although their relative amplitudes can vary slightly. For instance, the magnitudes of talking and swallowing signals increase as the mounting location approaches the larynx and upper oesophageal sphincter. The magnitudes of walking signals are invariant with position, as might be expected. Biological features across different subjects, including the fundamental frequencies of speech[47], the thickness of the skin and other aspects, lead to differences in the signal in ways that are expected and do not affect approaches in signal analysis and interpretation.

In practice, MA measurements consist of data streams that superpose physiological information from a multitude of sources. A processing flow that exploits the characteristic time-frequency features demonstrated in Fig. 2 enables separation of key events, each of relevance in medical and/or fitness monitoring, that is, energy expenditure (EE), heart rate (HR), respiration rate (RR), swallow counts (SC) and talking time (TT) (Fig. 3a).

Application of these strategies on the data in Fig. 2 demonstrates the scheme (Fig. 3b–f). Fig. 3b summarizes the EE over 2 s, with a 50% overlapping moving-average window as a sum of all-axis low-frequency (1–10 Hz) band-limited root-mean square (BLRMS) data[48]. The result enables classification of activity levels from low (sitting, ~$10^{-2}g$) to medium (walking, ~$10^{-1}g$) to high (jumping, ~$10^{0}g$) on a logarithmic scale.

Analysis of HR begins with the application of a bandpass filter ($f_{\mathrm{low}}=20$ Hz, $f_{\mathrm{high}}=50$ Hz; f_{low} and f_{high} are the low and high cut-off frequency, respectively) to the z-axis acceleration data to suppress noise outside the frequency range of interest. Cardiac pulses correspond to local maxima higher than 0.005g in the time series of these band-passed signals, ignoring intervals shorter than 0.33 s (~180 beats per minute (BPM)) and longer than 1.2 s (~50 BPM). Applying a 5 s, 50% overlapping moving window average to peak-to-peak intervals yields a running estimate of HR (Fig. 3c). The peak-detection algorithm, however, cannot operate reliably with motion artefacts that involve large impacts and associated temporal and spectral features that coincide with those due to comparatively subtle cardiac mechanics.

Measurements of RR are particularly sensitive to ambulatory signals due to overlaps of these two types of signals in the frequency domain (0.1–1 Hz). Traditional methods rely on three-axis accelerometers mounted on the chest or the abdomen and allow determination of RR only during periods that exclude effects of locomotion[15,16,49]. Simple or weighted-sum methods (for example, principal component analysis) can make use of the multi-axis information[17]. In the approach reported here, a noise-subtraction algorithm exploits time-synchronized three-axis acceleration measurements to extract respiration signals at all activity levels. The detection mechanism relies critically on the SN mounting location and orientation (Fig. 1a,b), where the z-axis and x-axis measurements are both sensitive to chest wall motion, whereas the y-axis acceleration is mainly associated with core-body motions. A wavelet-transform projection yields common mode z' values between z- and x-axis measurements. The differential mode z'' between z' and y-axis measurements decouple motions from respiration. In each pair of projection, we retain wavelet transform coefficients with coherence larger than 0.8 (Supplementary Note 4).

Figure 3d compares the band-passed ($f_{\mathrm{low}}=0.1$ Hz, $f_{\mathrm{high}}=1$ Hz) z-axis measurement with z''. Unlike traditional time-frequency analysis approaches for RR[50,51], a search for zero-crossing nodes of z'' determines the average time span of inspiration–expiration cycles $\bar{T}$ in 1 min, as the basis for estimating RR as $60/\bar{T}$ BPM (Fig. 3d). The direct counting method accounts for the time non-stationary nature of respiration during physical activities. An adaptive threshold of 10% of the s.d. of the data helps reduce miscounting associated with small-amplitude and fast-ripple features on top of the overall 1-min respiration pattern (Fig. 3d and Supplementary Note 4).

Signals that arise from speech involve the prominent presence of a second harmonic of the fundamental frequency f_0^1 in the expected frequency range and magnitude (Fig. 3e). The talking time detected in this manner appears as shaded regions in Fig. 3e. Using our device to determine TT has distinct advantages over methods that rely on microphones due to its insensitivity to airborne acoustics. Tests in controlled, acoustically isolated rooms show that external sounds at 100 Hz and 90 dB(Z), appear as signals with amplitudes of only $2\times10^{-2}g\,\mathrm{Hz}^{-1/2}$ (Supplementary Fig. 12), whereas speech at a similar frequency and at 65 dB(Z) on microphone (near the audible threshold) appears on the device with maximum amplitude of $10^{-1}g\,\mathrm{Hz}^{-1/2}$ (Supplementary Fig. 13). The effects of ambient sounds can therefore be neglected entirely in almost all practical scenarios.

Swallowing events feature both low-frequency mechanical motions (0.1–5 Hz) and high-frequency acoustic components (100–800 Hz). On the basis of this observation, the algorithm for SC detects swallowing events as high-frequency and low-frequency peaks that occur, coincidentally, within a 2-s time window (Fig. 3f). For the purpose of this algorithm, swallowing events are only considered if they are separated by more than 0.2 s from talking events and by more than 0.5 s from active periods (EE, > 0.05g).

Human subject evaluations in practical scenarios. Field studies in physical exercise and in dining demonstrate these data acquisition and processing schemes. The physical exercise study involves cycling and resting on a stationary bike, with HR between 50 to 180 BPM. A Polar hand-grip monitor yields reference HR values every 5 s (Fig. 4a). In a separate set of experiments, subjects manually count the number of breathing cycles per 5 min during normal sitting, walking and running activities as a reference for RR. For dining, each subject talks and swallows for 5 min according to a prescribed protocol. Here, periodicity (with a time scale of ~10 s, significantly longer than the time scale of event detection of ~0.1 s) in the activities facilitates tracking of numbers of events. In each minute of the nth test ($n=0$ to 5), the subject talks for $n\times10$ s, then swallows at $(n+k)\times10$ s, where $k=1$ to $6-n$. During data acquisition, each subject marks the start and end of the talking period as well as swallowing instances using logging buttons on an app that runs on the smartphone used for data acquisition (Fig. 1d). The dataset includes five subjects for each scenario (Supplementary Table 1). For the cycling test, each subject cycles for 5 min. Applying a 5-s, zero-overlapping moving window generates a total of 301 samples for comparison. RR experiments yield 56 samples across different activity levels, wherein each sample is an average RR over one 5-min test. A total of 26 dining tests generate average values for TT and SC over each 5-min test.

Figure 4a–c shows example results of MA measurements versus reference data. In the exercise scheme, the MA HR follows the reference HR from 100 to 160 BPM over a time period of 5 min under cycling activity, as in Fig. 4a. In addition to HR, the MA device captures the amplitude of the cardiac activity, which exhibits an approximate linear correlation to HR. In Fig. 4b, the MA RR follows the manually counted RR for this 2-min segment during walking. The mean RR values in both cases, marked by the dashed lines, match closely. Figure 4c is a 1-min demonstration of the dining scheme. The MA talking and swallowing events agree with the label reference.

Figure 4d shows Bland–Altman plots for HR, RR, TT and SC. HR has a mean difference of 2.8 BPM and a s.d. of the difference between HR measurement and HR reference (A_{RMS}) of 6.5 BPM. This limit of agreement is comparable to that observed with some of the best commercial devices for HR monitoring during physical activity ($A_{RMS}=4$ to 29 BPM). RR has a mean difference of 0.3 BPM and a s.d. of 2.5 BPM. As with HR, this difference is comparable to that of conventional monitors of RR ($A_{RMS}=2$ to 3 BPM). A categorized statistical analysis indicates that the s.d. increases slightly with intensity of the activity (Supplementary Fig. 14). TT has a mean difference of $-2.0\,\mathrm{s\,min^{-1}}$ and a s.d. of $2.2\,\mathrm{s\,min^{-1}}$. SC has a mean difference of −0.7 counts per 5 min and a s.d. of 2.8 counts per 5 min.

Sleep studies. Use of MA devices to quantify patterns of sleep represents a potential application in advanced clinical diagnostics. Figure 5a shows a subject equipped with an MA device on the SN and with a complete suite of conventional polysomnography (PSG) sensors for gold-standard reference measurements. A sleep-laboratory technician performs visual observations alongside throughout the study to record changes in body orientation. In addition to HR and RR detection, the MA device also monitors quasi-static body orientation continuously, following calculations for a rotation matrix R that transforms gravity measurements in the canonical frame $g=(0,0,-g_0)$ to the device frame $g'=(a_x, a_y, a_z)$, that is $g'=Rg$ (Supplementary Note 5).

Figure 5b shows an avatar representation of the subject in a left-recumbent position, along with the corresponding device and global frames of reference. The conversion of the rotation matrix to the Euler angles around the body-fixed (intrinsic) axis in z–y–x sequence (MATLAB function rotm2eul) better illustrates the

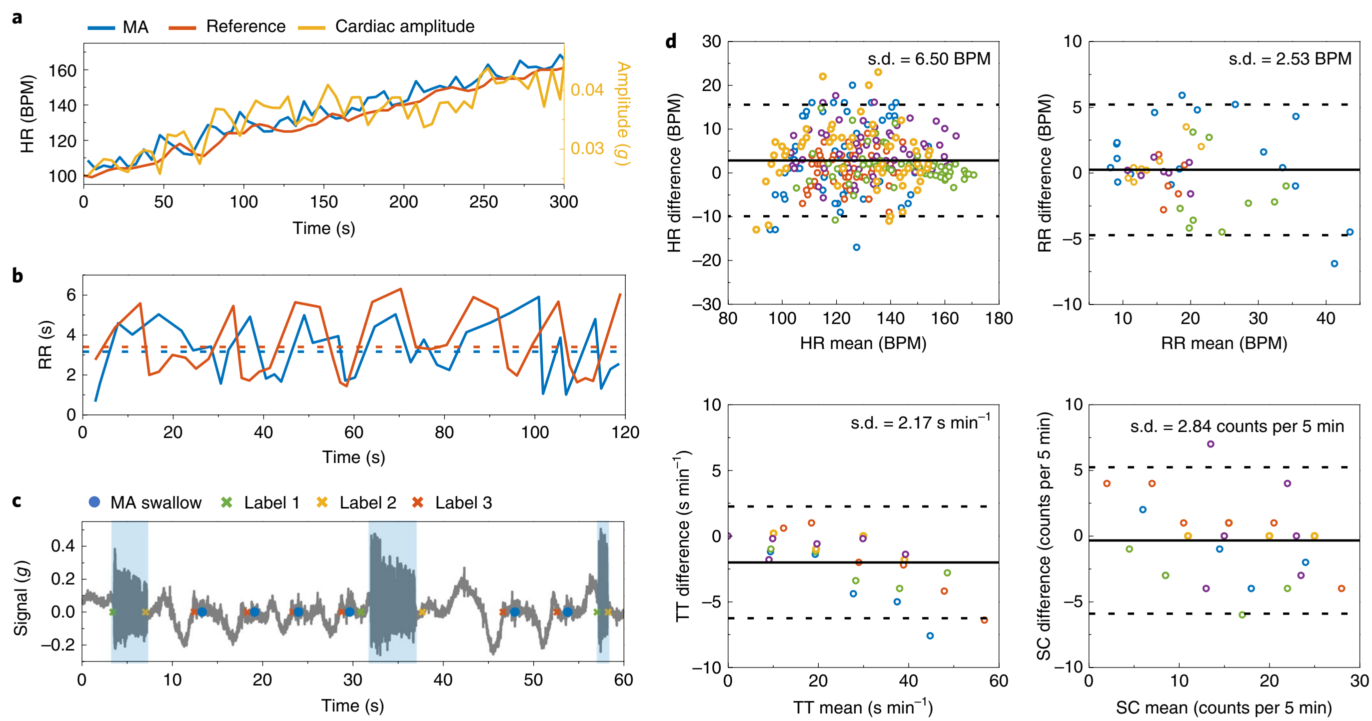

Fig. 4 | Results from MA data recorded at the SN in field studies with comparisons to reference measurements. a, HR measurements during a 5 min interval during exercise to increase the HR using MA signals and a Polar hand-grip monitor. The cardiac amplitude, measured as the peak acceleration amplitude, exhibits a correlation with the HR measurement. **b**, RR measurements during a 2 min interval using MA data and manual counting. The subject counts peak-to-peak intervals but the algorithm counts zero-to-zero intervals, thereby leading to a difference that appears as a time lag. **c**, A sample 1 min dining-scheme experiment comparing the reference labelling of events (cross) with the MA device detection (dot). Labels 1 and 2 mark the start and end of talking, respectively, while label 3 marks the occurrence of swallowing. **d**, The Bland–Altman analysis for HR, RR, TT and SC. The solid and dashed lines represent mean difference and 1.96 × s.d. of the difference between MA measurements and reference values, respectively. Different colours represent the five healthy subjects.

rotation operation. The rotation angle θ around the longitudinal x axis characterizes the major body orientation of interest during sleep, where we define zero degree as supine and the positive sense as turning right (left-hand rule). Figure 5c presents a calibration test on rotation angles, in which a subject rolls into a series of body orientations. In addition to the supine, prone, left-recumbent and right-recumbent positions, the MA signal at the SN reveals additional information associated with the relative rotation of the head against the torso (Figs. 1a and 5c). Figure 5d–f compares HR measurements from MA devices with HR derived from electrocardiography (1-min window, 50% overlap), RR derived from PTAF (2-min window, 75% overlap) and sleep technician inspection measurements of body orientation (0.1-s window, 0% overlap) throughout a ~7-h sleep study on a healthy male (age 26, Korean) subject. Bland–Altman analysis for HR and RR gives a s.d. error of 3.9 BPM and 2.6 BPM, respectively (Supplementary Fig. 15).

As a routine part of clinical care, segments of sleep are classified into four different stages, excluding the wake stage. The duration and frequency of each stage determines the sleep quality. The four stages are rapid eye movement (REM), and non-REM stages N1, N2 and N3. REM sleep comprises irregular and high RR and HR, along with the large amplitude EOG signals recorded using the PSG suite[52]. Non-REM sleep stages are defined by characteristic features on EEG, and although the MA device does not record EEG or EOG data, the results in Fig. 5g suggest that it has some capabilities in quantifying sleep stages by applying machine learning algorithms on MA data obtained during stages determined manually by a clinical expert.

Here, a hidden Markov model determines sleep stages as generative sequences characterized by a set of observable sequences with an underlying probabilistic dependence (Supplementary Note 6). The algorithm exploits multiband z-axis signal power on logarithmic scales as the observable clustering features, with a multiband choice featuring 0.1–0.8 Hz for respiration signals, sub-bands in the range 0.8–20 Hz for motions and 20–80 Hz for cardiac signals. As shown in Fig. 5g, the optimized inferred hidden states capture the overall trend of gold-standard sleep scoring. The success rate for a simple binary wake/asleep classification is 82%. Supplementary Fig. 16 includes a complete confusion matrix for multiclasses. Advanced analytics, a subject of ongoing work, may enable further classification.

The wireless operation and the ability to track sleep with a single device facilitates use in home settings and in a way that does not alter natural patterns of sleep—significant advantages over PSG systems. Insights obtained in this way can guide behaviours to optimize sleep quality. For example, Fig. 6a shows the cumulative distributive function (CDF) of HR and RR statistics, extracted from data collected from eight healthy subjects over five nights of sleep in the home, classified into four body orientations (supine: $-45° < \Theta < 45°$, left: $-135° < \Theta < -45°$, right: $45° < \Theta < 135°$, prone: $\Theta > 135°$ or $\Theta < -135°$. The solid lines are mean CDF values for all subjects. The shaded regions mark the s.d. variance between subjects (Fig. 6a). The inset compares the mean and s.d. of HR and RR respectively generated from the averaged CDF for different body orientations. The results indicate that the HR is highest, on average, in left-recumbent–prone-approximate positions. The RR is higher in recumbent positions but lower in prone positions, with supine as a reference. According to previous studies[53–55], such changes may relate to reductions in venous flow, with resulting blood pressure reductions and/or increases in reflexive sympathetic nervous activity.

As expected, the device is also sensitive to snoring signals. Figure 6b shows time-series and time-frequency analysis of a

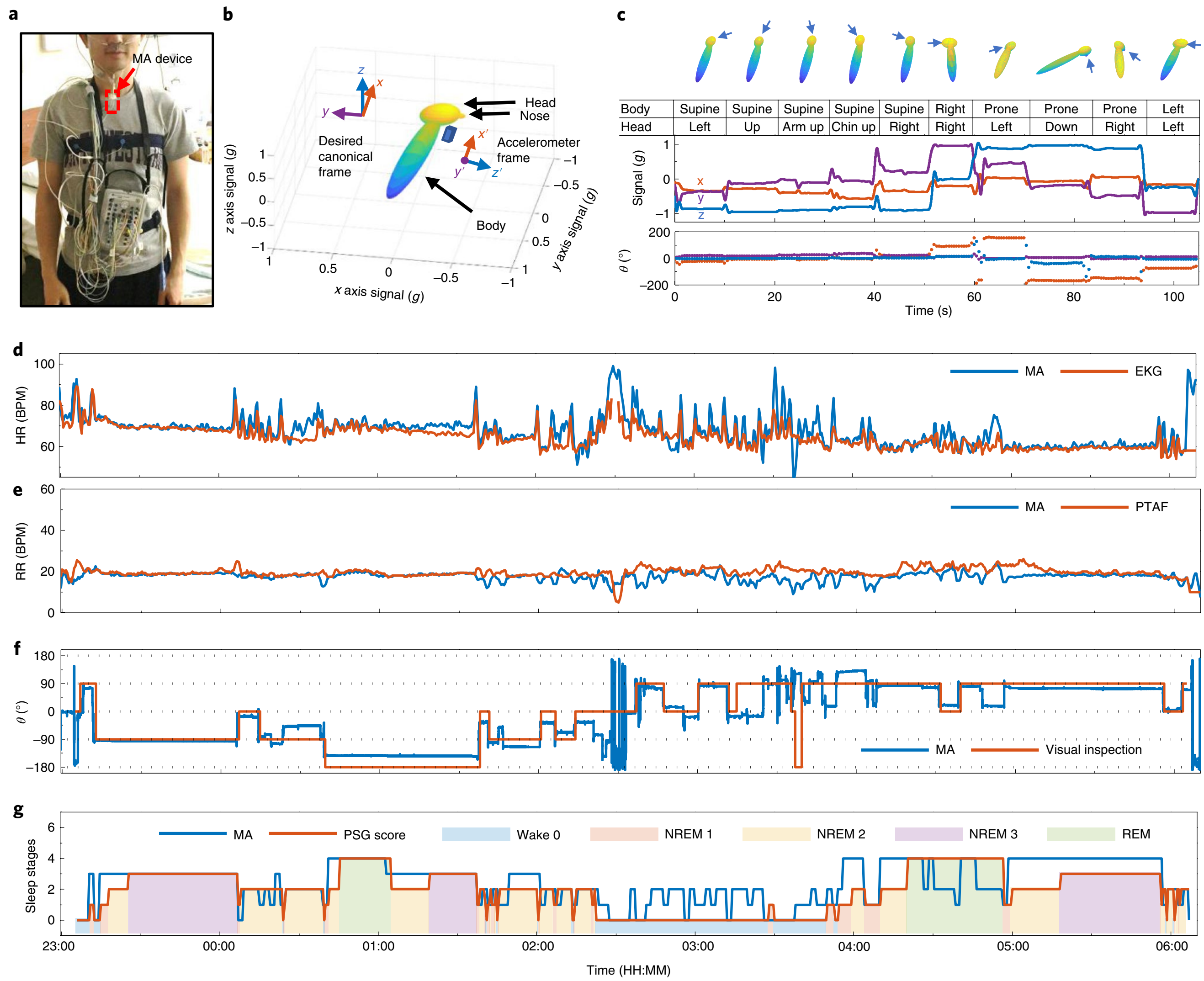

Fig. 5 | Application of MA sensing from the SN in clinical sleep studies. a, Image of the MA device on the SN (red box) along with a gold-standard PSG sensor ensemble, including devices for recording electrocardiograms (ECGs), electroencephalograms (EEGs) and electrooculograms (EOGs), and for pressure transducer air flow (PTAF) measurements, along with an abdomen strain gauge, thorax strain gauge and thermistor. **b**, Avatar representation of a subject with the associated device frame and canonical frame (colouring represents 3D rendering and is for illustrative purposes only). **c**, Body-orientation calibration test. The arrows indicate the position of the nose. **d**, Comparisons of HR determined with the MA sensor and with the ECG recordings during sleep. **e**, Comparisons of the RR determined with the MA sensor and with the nasal PTAF recordings during sleep. **f**, Comparisons of the body orientation determined with the MA sensor and by visual inspection by a sleep technician. **g**, Inference of sleep stages on the basis of multiband *z*-axis signal power of MA measurements compared with clinically determined sleep stages.

representative ~50 s period of snoring followed by a transition to a ~50 s period of quiet sleep from a healthy female subject. The time series superimposes the band-stopped (($f_{low}=1$ Hz, $f_{high}=60$ Hz) *z*-axis acceleration measurement with the band-passed ($f_{low}=0.1$ Hz, $f_{high}=1$ Hz) respiration signal, to show that snoring occurs during exhalation. The snoring-to-quiet transition in the sample of Fig. 6b correlates with a slight leftward head versus torso rotation of ~10. The time-frequency analysis shows a clear presence of harmonics with fundamental frequency of ~50 Hz, which falls in the range of the natural frequencies of the soft palate and tongue structures[56,57]. The TT algorithm can be adapted to search for snoring time (ST) by shifting the fundamental frequency search range to the lower frequencies $\left(20\,\text{Hz}<f_0^1<80\,\text{Hz}\right)$. The auto-detected ST appears as shaded regions of the spectrogram plot. A tendency for snoring occurs during inspiration due to the Bernoulli effect[58]. As the throat starts to narrow, the velocity of flow may increase which decreases the pressure in the airway behind the tongue and soft palate, thereby drawing the tissues together. The timing relative to the inspiration period may indicate the anatomical origin of snoring: tongue, or soft palate. Figure 6c compares the snoring signal generated by these two different mechanisms. From 0 to 16 s, the subject artificially obstructs the airway by pushing the tongue to the back of the throat, then the subject artificially generates the snoring sound by vibrating the soft palate. The results clearly demonstrate that tongue snoring has inconsistent timing relative to the respiration cycle as compared to soft palate snoring. Moreover, the spectrogram illustrates that snoring generated by the tongue appears at a higher frequency range than that of the soft palate, as might be expected based on the mechanics of these processes.

Discussion

This paper summarizes a comprehensive set of concepts in hardware design and data analytics as the basis for an unusual class of soft, wireless MA sensor designed to operate on the SN, as a location

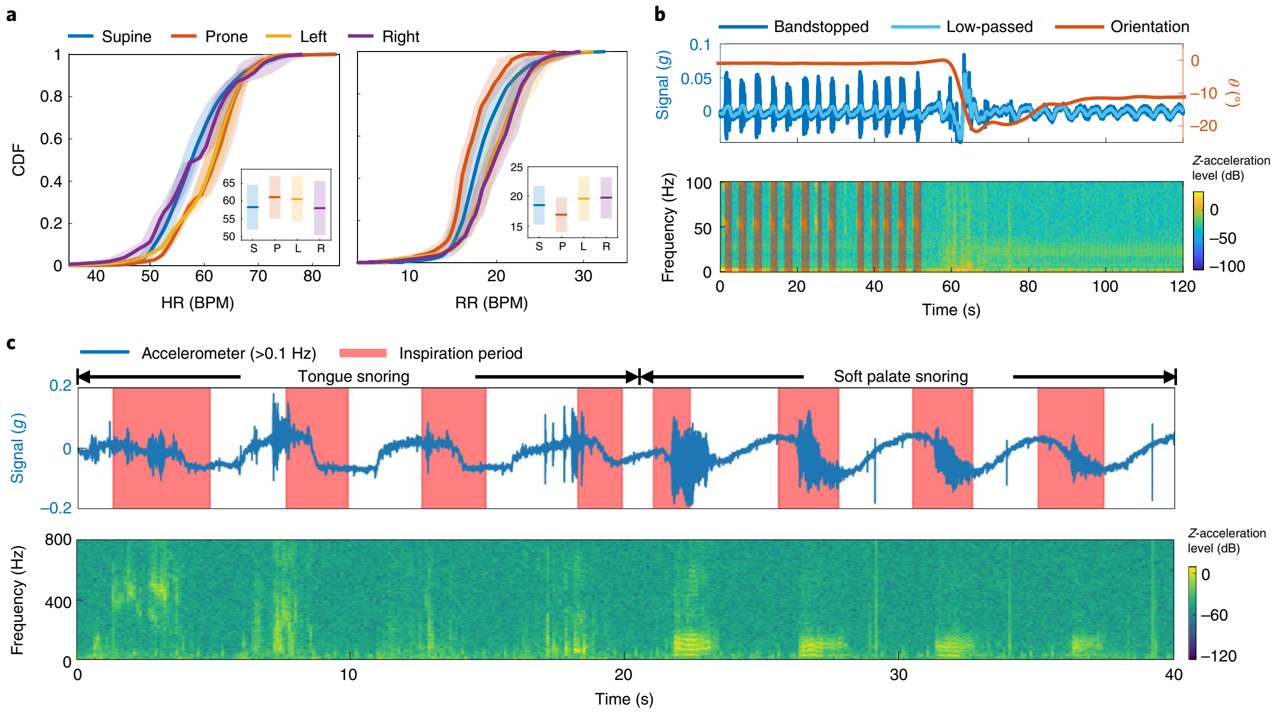

Fig. 6 | Insights into sleep patterns determined by MA sensing from the SN. a, CDF of HR and RR in supine (S), prone (P), left (L) and right (R) body orientations. Inset: indication of the mean (line) and s.d. (bars) of the measurements between subjects. **b**, Sample data that illustrate the transition from snoring to quiet periods, plotted along with body orientation. **c**, Comparisons of different types of snoring mechanisms and their characteristics in acceleration and frequency.

that enables collection of a unique set of multimodal data related to a range of physiological processes. Specific demonstrations in various practical scenarios show capabilities for simultaneously monitoring HR, TT, RR, SC and EE through data algorithms that exploit time- and frequency-domain representations, with additional possibilities in tracking body orientation, steps and gait, coughing events, respiratory sounds and many others. By design, the technologies and methods described here align well with current manufacturing practices and commercial components, thereby offering a high level of technology readiness. Increasing the range and sensitivity of the accelerometers and designing systems that incorporate multiple different types of accelerometers both have the potential to improve the functionality and expand the types of addressable applications.

Unresolved challenges for continuous monitoring include those that involve motion artefacts in cardiac signal and respiratory rate detection. Semi-continuous monitoring can, however, be accomplished by opportunistic sensing during times when such artefacts are absent[14]. Incorporating multinodal MA detection approaches represents an alternative route for signal decomposition and precise measurements of cardiac mechanics[14,59]. The use of improved reference measurement methods in an ambulatory environment under intense and natural activities may aid in further development of data analytics approaches. Multimodal sensing enabled by the addition of strain gauges, for example, could enhance the accuracy in determining parameters, such as the respiration rate, that can be affected by low-frequency noise and motion artefacts. Evaluating signals under an expanded variety of daily activities with additional participants, improving analysis algorithms for enhanced performance and developing classification methods for a broader range of MA signals are interesting directions for future research.

The monitoring of sleep appears to be an important area of potential application, with significant advantages compared to both polysomnography systems and conventional wrist-mounted wearables. Others include uses in hospitals for monitoring surgical recovery, particularly in paediatric populations, in assisted living environments to track social engagements, and in speech and physical therapy to treat aphasia and dysphagia. The straightforward addition of sensor modalities beyond accelerometry, such as pulse oximeters, could further expand the fields of use.

Methods

Fabrication of the electronics. Fabrication began with patterning a sheet of fPCB (12-µm-thick top and bottom Cu layer, 25-µm-thick middle polyimide layer, AP7164R, DuPont) into the necessary shapes using a ultraviolet laser cutter (LPKF U4). A CO_2 laser cutter (VLS3.50) defined pieces of FR4 board (0.381 mm, McMaster Carr 1331T37) into geometries matched to half of the sizes of the two electronic islands (Fig. 1b). Folding the island regions of the fPCB around the FR4 and bonding them in place using an adhesive (Loctite Tak Pak 444) yielded a dual-sided structure. Solder paste (Chip Quik TS391LT) joined the various electronic and sensor components onto the fPCB by reflow using a heat gun (AOYUE Int866).

Design of the encapsulating enclosure. A thin (~0.3 mm) elastomeric membrane of silicone (modulus, 60 kPa; toughness, 500 MPa) moulded into a preformed shape bonds on top of the planar silicone substrate around its perimeter to form a hollow enclosure that protects the system from the environment. This design provides a waterproof encapsulation structure that also allows free movement of the buckled serpentine interconnects (Supplementary Fig. 17). The device shows no degradation in performance after complete immersion in phosphate buffered saline solution at 70 °C for ten days. Compared with a conventional, solid-core encapsulation strategy, the hollow air-pocket layout reduces the equivalent tensile modulus, bending and twisting stiffness by ~3.4, ~1.6, and ~2.5 times, respectively (Supplementary Figs. 4 and 5d–f). Indeed, the equivalent tensile modulus is only ~18 kPa, nearly seven times lower than that of human skin (120 kPa)[60]. The bending and twisting stiffnesses (~17.2 Nmm^2 and ~59.4 Nmm^2, respectively) are ~2.5 and ~3.9 times lower than those of the skin with comparable thickness.

A layer of a soft silicone gel (Silbione 4717 Gel A/B, Elkem) at the base of the system but within the encapsulating structure provides a degree of mechanical isolation from the underlying skin, where stresses would otherwise accumulate at the locations of the islands during motions and/or deformations of the body and skin. Simulations indicate that the shear and normal interfacial stresses remain below the threshold for sensation (~20 kPa) for deformations of the skin to tensile strains of up to 30% when the thickness of the gel is 400 µm (Supplementary Figs. 18 and 19). Without the strain-isolation layer, the stresses reach 20 kPa at strains of only 10% (Supplementary Fig. 20). This strain-isolation layer does not, however, extend to the region of the device that supports the accelerometer, thereby ensuring its intimate mechanical coupling to the skin. The result enables high fidelity in MA measurements, as demonstrated by comparing data recorded using this device with those captured using the same accelerometer but in an isolated form connected by fine wires to external data acquisition electronics. Evaluations involve both systems on a vibrational stage or on a planar speaker, programmed to move in a sinusoidal manner with a frequency between 1 Hz to 100 Hz and between 100 Hz to 800 Hz, respectively (Supplementary Fig. 6). The measured responses are nearly identical in the frequency range of interest (0–800 Hz) except for a maximum of ~13% drop in the relative response around 91 Hz. Similar measurements show that the responses of the device are not significantly affected by stretching to tensile strains of 12% (Supplementary Fig. 21). Supplementary Fig. 7 summarizes an analytic model for the device on the skin (Supplementary Note 3). For frequencies between 1 and 50 Hz (Supplementary Fig. 8), the difference in the acceleration of skin with and without the device is less than 3%, due to the small mass (4.56 g) of the device.

Assembly of the device. A three-axis milling machine (Roland MDX 540) created aluminium moulds in geometries defined by three-dimensional computer-aided design drawings created using ProE Creo 3.0. The capping membrane was defined by casting a silicone thermoset polymer into the gap formed by matching pairs of moulds (Ecoflex, 00–30, smooth-on) with well controlled thickness (300 µm). Curing occurred in an oven at 70 °C for 15 min. The air cavity that enclosed the electronics was defined by bonding this membrane to a planar silicone substrate film around the perimeter.

Silicone gel (Silbione RT Gel 4717 A/B, Bluestar Silicone, Young's modulus (E) = 5 kPa) served as a strain-isolation layer at the base of the device. A manual screen-printing process delivered this material onto the substrate film in a pattern to match geometries of the islands. Heating on a hot plate at 100 °C for 5 min cured the gel. Fabrication was completed by delivering the electronics in aligned fashion onto this gel and capping the entire structure with the membrane.

Characterization of the device performance. Characterization focused on fully integrated devices and isolated accelerometers connected to external data acquisition electronics with fine wires (36 gauge). An acrylic silicone served as a bonding adhesive (3M, 2477p) to the centre of a speaker (JBL Go Portable 1) or to a vibration stage (3B Scientific) in both cases. The vibration stage and speaker were programmed to execute frequency sweeps from 1 to 100 Hz and from 100 to 800 Hz, respectively.

Data collection. The SN served as the mounting location in all cases. For the swallowing experiment, the duration of each session was 5 min. The subject talked and swallowed water for a prescribed number of times per minute throughout the session. The talking duration was 10 s per session, and the swallowing occurred every 10 s from the end of a previous talking session to the start of a subsequent one.

For the HR-monitoring session, the subject rode a cycling machine with a HR sensor interfaced to electrodes on the handle. The session began when the HR reached over 90 BPM. The subject cycled to increase the HR by 10 BPM each minute until reaching 170 BPM, as shown in the Fig. 4a.

For the sleep study, in addition to the MA device, the subject wore a suite of PSG sensors, including a three-channel system for EEG on the forehead, two channel leads for electrocardiography on the chest, a pair of leads for electromyography on the chin, a pair of channels for EOG on the side of upper left eye and lower right eye, a PTAF with thermistor in the nostrils and two strain-gauge bands around the chest and abdomen.

For all the studies, the participant gave informed consent.

Data analytics. All analysis used the MATLAB (R2018b) technical computing language. All digital manipulation uses a fourth order Butterworth infinite impulse response filter followed by a non-causal, zero-phase filtering approach (MATLAB function filtfilt). Identification of sleep stages used Python 3.0, with sci-kit learn and hmm learn packages.

Voice signal detection using harmonics. Given that $P(f_0^1)$ is a local maximum of power spectral density $P(f)$ in the range of the human voice ($f_0^1 < 160$ Hz for male subjects, 150 Hz $< f_0^1 <$ 400 Hz for female subjects) (Fig. 3e), the algorithm searches for a local maximum $P(f_0^2)$ in the frequency range $\frac{3}{2}f_0^1 < f_0^2 < \frac{7}{2}f_0^1$ and identifies speech if the search matches the anticipated harmonics behaviour within a tolerance distance $|f_0^2 - 2f_0^1| \leq 10$ Hz. Instances with $f_0^2 < 120$ Hz and $P(f_0^2) < 5\times10^{-3} g\,\mathrm{Hz}^{-1/2}$ are not considered.

Classifying active and inactive states. Identification of active versus inactive states uses a fixed threshold of 0.05 $g = \bar{s} + 5\delta s$, where s is the first 30 s of EE measurement as the subject sits quietly with minor movements, and $\bar{s} \approx 0.012\ g$ and $\delta s \approx 0.008\ g$ are the characteristic mean and s.d. of s..

Mechanics of swallow-event detection. This criterion allows for only one high-frequency peak to be paired with the temporally closest low-frequency peak. Evaluating the stochastic differential of the signal zeros the quasi-static offset before the data pass through the low-pass filter. The algorithm then locates local maxima in the resulting time series of minimum peak prominences of $5\times10^{-4}g$, a minimum peak distance of 1 s and a maximum peak width at half maximum of 0.5 s. High-passed peaks are detected with a minimum peak height of $0.024g \approx 5A_{BLRMS}$, where A_{BLRMS} is the high-frequency (100–800 Hz) BLRMS of quiet-time signals.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability
The main data supporting the results in this study are available within the paper and its Supplementary Information. The raw and analysed datasets generated for the studies in Figs. 2–6 are available for research purposes from the corresponding authors upon reasonable request.

Code availability
The codes used for the embedded system and data collection are available on GitHub at https://github.com/johnrogersgroup/Wireless_MA. The analysis codes used in this study are available from the authors upon request.

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Author contributions

K.L., Z.X. and J.A.R. performed the structural design of the system. Z.X., R.A., Y.D. and Y.H. performed mechanical and electromagnetic modelling and theoretical studies. K.L., J.Y.L., J.H.L., J.B.P. and J.K. developed the embedded system and the user interface. K.L., X.N. and J.A.R. designed and performed the experimental studies on the technology. X.N., K.L. and J.A.R. designed and performed the human subject studies. X.N., K.L., M.I., R.L.E., D.J.P. and D.H.K developed the signal-processing algorithms and performed the data analysis. K.L., H.A., D.J.P., H.U.C., O.O.O., S.G., E.C., M.H., J.B., H.J., C.L., S.B.K., S.M., J.T.R and I.H. manufactured the devices. S.X., A.T. and C.R.D. provided clinical advice. X.N. and J.A.R. wrote the signal processing algorithm part of the manuscript. K.L., X.N., Z.X., Y.H. and J.A.R. contributed to the other sections.

Competing interests

The authors declare no competing interests.

Additional information

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Sample size	No sample size calculation was performed. A sample size of 5 provides sufficient information on the repeatability of different types of mechanical and vibratory signals.
Data exclusions	No data were excluded from the analyses.
Replication	The mechanoacoustic recordings were repeated more than ten times. The results were replicable, and any small discrepancy in the data were displayed explicitly.
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Population characteristics	Participants in the experiments were healthy subjects.
Recruitment	The participants were recruited by the Materials Science and Engineering and Biomedical Engineering at Northwestern University. The participants for the sleep study were two of the investigators, who volunteered to be subjects. There were no self-selection biases or other biases.
Ethics oversight	Human-subject participation was entirely voluntary. The devices used are considered to carry minimal risk, and therefore approval was not needed.

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