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A Novel Method for Tracking Neck Motions Using a Skin-Conformable Wireless Accelerometer: A Pilot Study

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Keywords
Cervical spine · Rehabilitation · Digital health · Machine learning · Wearable electronics

Abstract
Introduction: Cervical spine disease is a leading cause of pain and disability. Degenerative conditions of the spine can result in neurologic compression of the cervical spinal cord or nerve roots and may be surgically treated with an anterior cervical discectomy and fusion (ACDF) in up to 137,000 people per year in the United States. A common sequelae of ACDF is reduced cervical range of motion (CROM) with patient-based complaints of stiffness and neck pain. Currently, tools for assessment of CROM are manual, subjective, and only intermittently utilized during doctor or physical therapy visits. We propose a skin-mountable acousto-mechanic sensor (ADvanced Acousto-Mechanic sensor; ADAM) as a tool for continuous neck motion monitoring in postoperative ACDF patients. We have developed and validated a machine learning neck motion classification algorithm to differentiate between eight neck motions (right/left rotation, right/left lateral bending, flexion, extension, retraction, protraction) in healthy normal subjects and patients. ***Methods:*** Sensor data from 12 healthy normal subjects and 5 patients were used to develop and validate a Convolutional Neural Network (CNN). ***Results:*** An average algorithm accuracy of 80.0 ± 3.8% was obtained for healthy normal subjects (94% for right rotation, 98% for left rotation, 65% for right lateral bending, 87% for left lateral bending, 89% for flexion, 77% for extension, 50% for retraction, 84% for protraction). An average accuracy of 67.5 ± 5.8% was obtained for patients. ***Discussion:*** ADAM, with our algorithm, may serve as a rehabilitation tool for neck motion monitoring in postoperative ACDF patients. Sensor-captured vital signs and other events (extubation, vocalization, physical therapy,

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walking) are potential metrics to be incorporated into our algorithm to offer more holistic monitoring of patients after cervical spine surgery.

Introduction

Neck pain is a highly prevalent problem with an estimated mean lifetime prevalence of 48.5% [1] and is the fourth leading cause of disability worldwide [2, 3]. Based on recent data from the Global Burden of Disease, Injuries, and Risk Factors Study 2017, the prevalence, incidence, and years lived with disability for neck pain have increased from 1990 to 2017 [4], highlighting neck pain as a significant public health problem and an increasing driver of healthcare utilization [5]. Common causes of neck pain include cervical degenerative disease, also known as cervical spondylosis, and cervical disc herniations. These conditions may also cause compression of the cervical spinal cord or cervical nerve roots, resulting in clinical symptoms of myelopathy and radiculopathy, respectively [6]. While many patients can be effectively treated without surgery [7], many patients with debilitating pain or neurological disability may undergo surgical treatment [8–10]. The most performed procedure to address cervical myelopathy and/or radiculopathy is an anterior cervical discectomy and fusion (ACDF).

Though ACDF is a safe and established procedure performed in up to 137,000 patients annually in the United States [11], patients often experience reduced cervical range of motion (CROM) postoperatively [12], which can be associated with discomfort, pain, and reduced patient satisfaction. To address reduced CROM, patients are often instructed to perform regular neck motion exercises in physical therapy (PT) as well as at home; however, substantial limitations exist in the widespread implementation of these modalities to improve patient outcomes at scale. For example, current methods of CROM measurement, such as using bulky inclinometer-based devices, vary widely in terms of ease of use, availability, and acceptance and often involve active surgeon and/or therapist measurements performed during scheduled in-person visits, providing only intermittent insights and limited patient real-time feedback. Sophisticated systems based on optoelectronic [13, 14], electromagnetic [15, 16], ultrasonic [17], and electrogoniometric [18, 19] technologies exist but require highly controlled environments and qualified staff for implementation and still do not provide continuous monitoring. Wearable piezoresistive textiles have demonstrated utility in measuring CROM [20] but have not been validated in clinical settings.

A soft, flexible, low-profile, skin-mountable, acoustomechanic sensor [21] (shown in Fig. 1), referred to as the ADvanced Acousto-Mechanic (ADAM) sensor, offers a promising solution for objective continuous monitoring of CROM in ACDF patients. ADAM has been accepted into the FDA’s Drug Development Tool Program and is undergoing full qualification and has also been submitted for CE Mark. When mounted at the suprasternal notch (SN), ADAM is capable of multiparametric measurements of a wide range of biological processes, from low-frequency processes like overall body motion and orientation to high-frequency processes like cardiac and respiratory activity [21]. ADAM has shown clinical utility in a variety of applications including monitoring dysphagia [22], objectively quantifying pruritis in atopic dermatitis [23, 24], cardiopulmonary monitoring in athletes [25], and, of recent interest, monitoring and screening for COVID-19 [26, 27]. In this work, we present and validate ADAM, in combination with artificial intelligence, as a novel rehabilitation tool for postoperative monitoring of ACDF patients with a focus on neck motion monitoring. The contributions of this study are as follows:

1. Development of a Convolutional Neural Network (CNN) algorithm in the healthy normal population to classify the following eight essential neck motions: right and left rotation, right and left lateral bending, flexion, extension, retraction, protraction
2. Evaluation of the CNN algorithm in a healthy normal population and postoperative ACDF patients
3. Application of a CNN algorithm to accelerometer and gyroscope data collected from the SN

Materials and Methods

Neck Motions of Interest

The eight neck motions of interest are shown in Figure 2a. Four neck motions (right and left rotation, flexion, extension) were deemed essential as they encompass most of the neck movement of daily activity that would be critical to regain for postoperative patients. The additional four neck motions (right and left lateral bending, retraction, protraction) are also clinically relevant and would be useful though not critical to measure. Lateral bending captures motion in the coronal plane. With rotation, flexion, and extension, the addition of lateral bending would allow analysis of motion in all three cardinal planes.

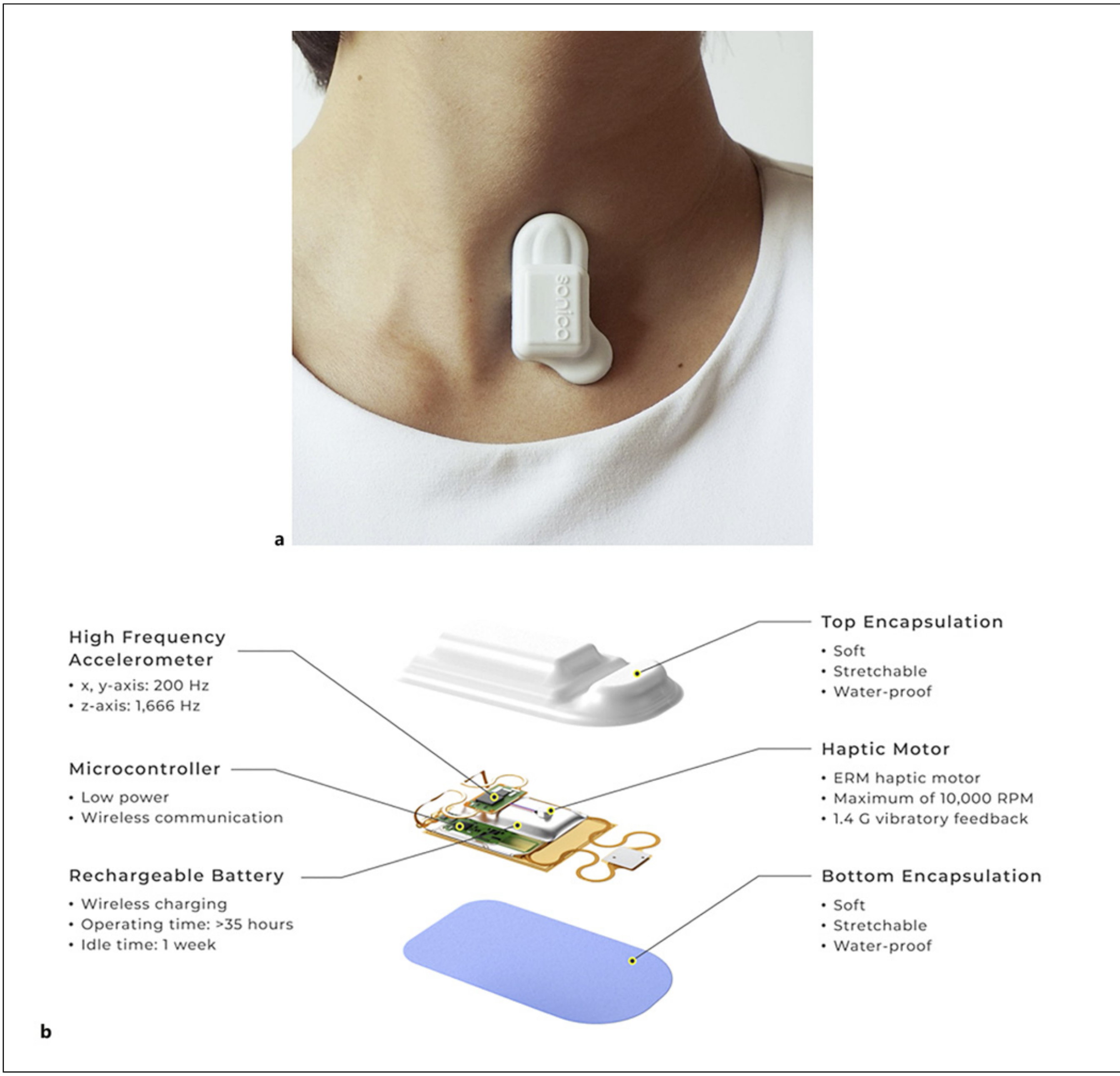

Fig. 1. a ADAM sensor placed on the SN. **b** Structure of ADAM sensor.

Data Collection

All participants, both healthy normal subjects and patients, provided written consent prior to participation in this study (see online suppl. Appendix A for demographic information; for all online suppl. material, see https://doi.org/10.1159/000536473). Study procedures were approved by the Northwestern University Institutional Review Board (STU00213413) and registered on ClinicalTrials.gov (NCT04921800). During data collection, participants wore ADAM at the SN (see online suppl. Appendix B1-2 for more details) that was placed by a member of the research team. Healthy normal candidates were students and laboratory staff older than 21 years old, without any history of neck conditions, and able to complete the study protocol without any pain or limitations. Patients were recruited from the Department of Orthopaedic Surgery at Northwestern Memorial Hospital. To ensure that all neck motions were performed accurately and adequately by all participants, a member of the research team supervised all data collection sessions and ensured good signal quality from real-time waveform outputs from the accelerometer and gyroscope on an iPhone app.

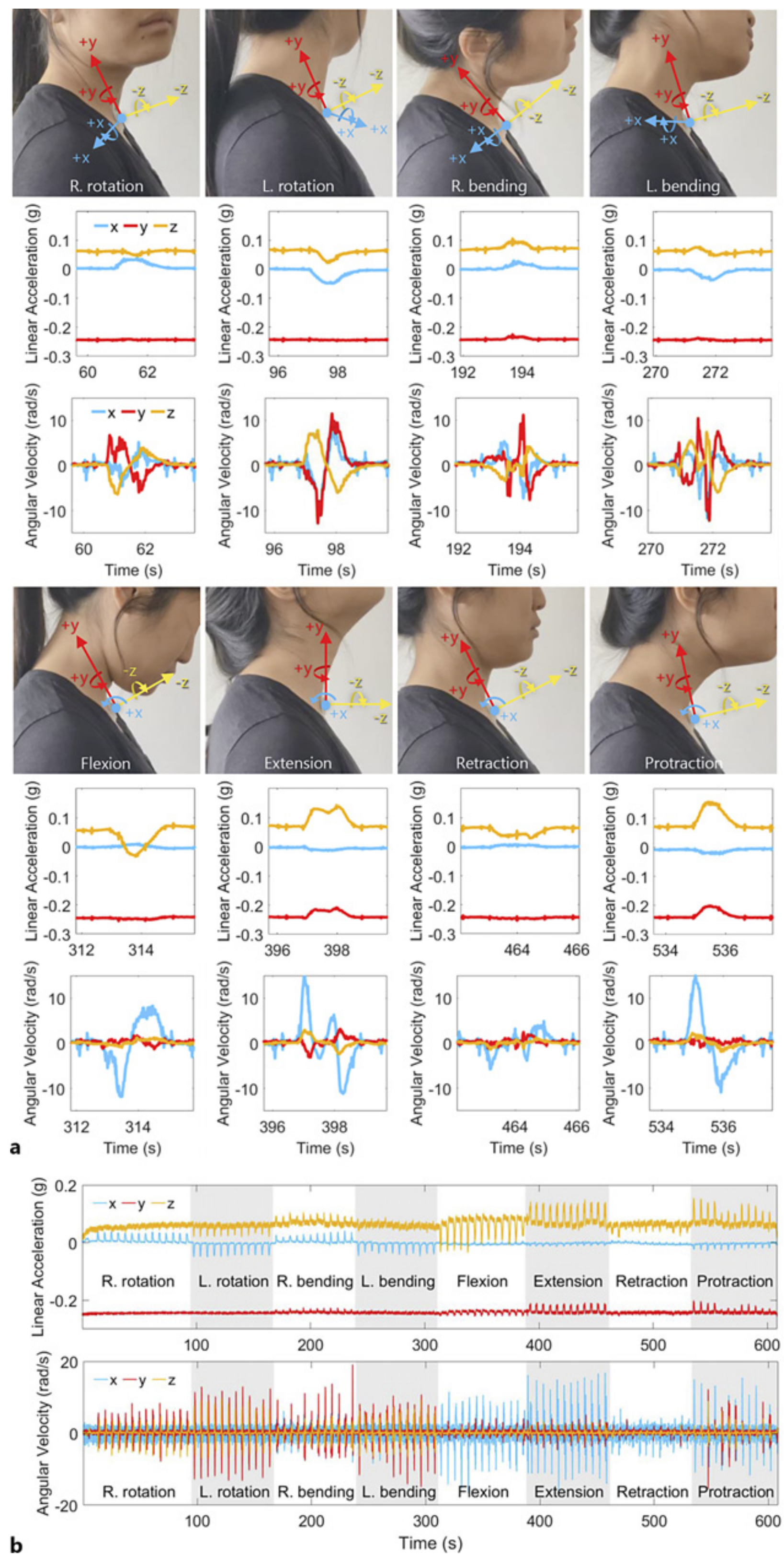

Fig. 2. a Motion signatures for right and left rotation, right and left lateral bending, flexion, extension, retraction, and protraction in a healthy normal subject. Arrows indicate orientation of x, y, and z linear accelerations and angular velocities from accelerometer and gyroscope, respectively. **b** Example of a data collection session for a healthy normal subject.

Algorithm Evaluation

Two types of algorithm evaluation were performed. The first type of evaluation was performed via a data resampling method called cross validation during the algorithm development process. The purpose of this evaluation was to improve and optimize the algorithm on the training data set prepared from healthy normal subjects. The second type of algorithm evaluation was performed to examine the generalizability of the algorithm to the patient population. In this evaluation, the machine learning algorithm that was trained using the healthy normal data set was applied to the patient data set (see online suppl. Appendix C for more details).

Results

The training data set for algorithm development and evaluation was collected from fourteen unique healthy normal subjects (24.50 ± 0.98 years old, 1:1 female-to-male ratio) in a controlled environment. During data collection, subjects sat upright in a chair, looking straight ahead with their neck in a neutral position, feet flat on the floor, and arms relaxed by their sides. The eight neck motions were demonstrated to the subject, and they were instructed to perform ten repetitions of each of the eight neck motions in the following sequence: right rotation, left rotation, right lateral bending, left lateral bending, flexion, extension, retraction, and protraction. ADAM was connected via Bluetooth with an iPhone to start data collection mode, and the subject was guided with verbal cues through the motions to facilitate smooth data collection. After the last repetition, the iPhone was used to end data collection mode. An initial set of neck motion samples was collected from thirteen healthy normal subjects, and additional samples were collected from a fourteenth healthy normal subject. For three healthy normal subjects, additional data were collected later in the algorithm development process to gather more varied data for algorithm optimization. Healthy normal subjects 1, 4, and 12 performed the neck motions at slower speeds. Healthy normal subject 1 performed neck motions in a reclined position. After reviewing the data, two subjects were excluded from the analysis due to poor signal quality from low-speed movements. A total of 960 neck motion samples from twelve healthy normal subjects were used in the analysis (as shown in Fig. 2, online suppl. Video 1).

The patient data set was collected to examine the generalizability of the algorithm to the patient population. Eleven patients (57 ± 11 years old, 7:4 female-to-male ratio) were recruited and consented for data collection. For each patient, data were collected in one continuous session lasting about 24 h. ADAM was placed on the SN by the surgeon and activated by a member of the research team before reversal of anesthesia and extubation. ADAM remained on the patient until discharge from the hospital the next day. Patients were then transported to the post-anesthesia care unit (PACU), where they were able to fully wake up from anesthesia. They remained in the PACU for a few hours until they were stable enough to transfer to a floor unit. Two attempts were made to carry out the range of motion (ROM) protocol, the first immediately after awaking in the PACU (baseline) and the second on the floor unit immediately prior to discharge (pre-discharge), as detailed below. These time points were chosen to capture neck motions spanning the full length of patients' hospital stay.

Patient ROM Protocol:

1. The eight neck motions were demonstrated to the patient
2. The patient was instructed to perform five repetitions of each of the eight neck motions to the best of their ability but not beyond the point of pain in the following sequence: right rotation, left rotation, right lateral bending, left lateral bending, flexion, extension, retraction, and protraction
3. The patient was guided with verbal cues through the motions to facilitate smooth data collection

Some patients were too drowsy in the PACU to perform the baseline ROM protocol; for those patients, they were able to perform the pre-discharge ROM protocol the next day. During the patients' 24-h hospitalization, time points were also noted by the patients' nurses for additional events that may be of interest to analyze, including extubation, first vocalization after surgery, eating and drinking, PT sessions, and walking. Thus, ADAM captured around 24 h of continuous data with the neck motions of the ROM protocols contained within. After reviewing the patient data, only 5 patients' data were used in the analysis. For one of the eleven consented patients, data collection mode on ADAM was not successfully activated, and no data were collected. For the other 5 patients who were excluded from our data analysis, the data's signal quality was limited due to the patients' pain and insufficient CROM. In the end, a total of 300 samples from 5 patients were used in the analysis (as shown in Fig. 3, online suppl. Video 2). All data collection sessions are summarized in Table 1.

Algorithm Evaluation Results

Leave-one-out cross validation was performed ten times on healthy normal subjects. In this evaluation, each motion constituted a single sample. An average accuracy of 80.0 ± 3.8% was obtained for neck motion

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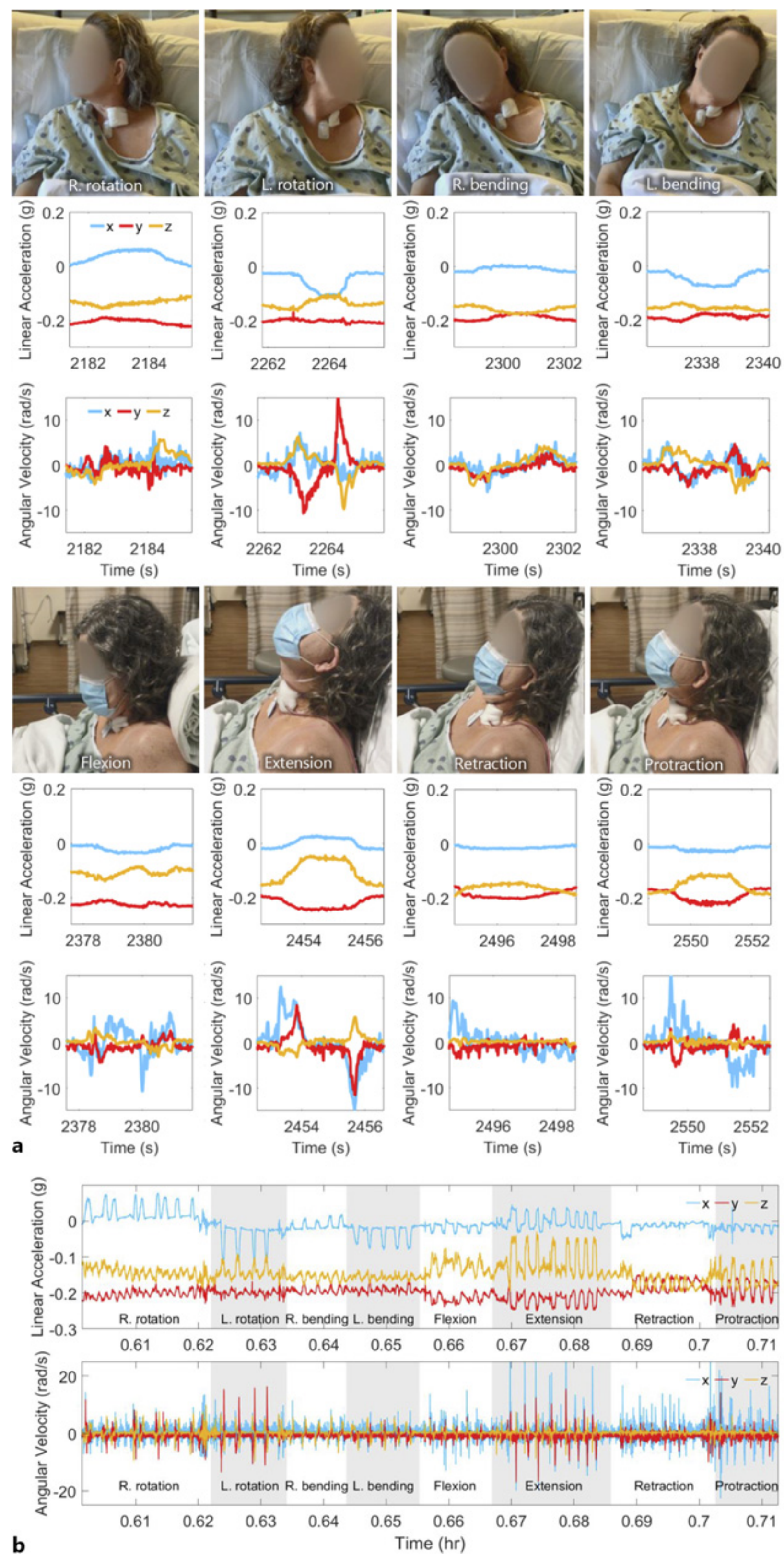

Fig. 3. a Motion signatures for right and left rotation, right and left lateral bending, flexion, extension, retraction, and protraction in a postoperative ACDF patient. Arrows indicate orientation of x, y, and z linear accelerations and angular velocities from accelerometer and gyroscope, respectively. **b** Example of a data collection session for ROM protocol for a postoperative ACDF patient.

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Table 1. Summary of data collected from healthy normal subjects and patients

Data collection session	Subject		Speed	Position	Number of Samples
1	Healthy normal subject ID	1	Fast	Upright	80
2		2	Fast	Upright	80
3		3	Fast	Upright	80
4		4	Fast	Upright	80
5		5	Fast	Upright	80
6		6	Fast	Upright	80
7		7	Fast	Upright	80
8		8	Fast	Upright	80
9		9	Fast	Upright	80
10		10	Fast	Upright	80
11		11	Fast	Upright	80
12		12	Fast	Upright	80
13		13	Fast	Upright	80
14		4	Slow	Upright	146
15		12	Slow	Upright	90
16		1	Slow	Upright	166
17		1	Varied	Reclined	160
18		1*	Varied	Upright	44
19		14*	Varied	Upright	36
20	Patient ID	1			80
21		2			40
22		6			40
23		7			40
24		8			80
25		9			80
26		10			80
27		11			40
					2,162

*Flexion only.

classification in healthy normal subjects (as shown in Fig. 4b). The classification accuracies for each individual neck motion were 94% for right rotation, 98% for left rotation, 65% for right lateral bending, 87% for left lateral bending, 89% for flexion, 77% for extension, 50% for retraction, and 84% for protraction (as shown in Fig. 4a).

A similar cross-study evaluation was performed for patient data. In this evaluation, the CNN model that was trained on the entire data set of healthy normal subjects was applied to patient subjects. The classification performance was measured ten times on each patient's data to compute the overall classification accuracy. An average accuracy of 67.5 ± 5.8% was obtained from the patient data set (as shown in Fig. 5).

Additional Events

A 24-h data collection session for a representative patient is shown in Figure 6a. Periods of sleep were identified as periods of relative inactivity (as shown in Fig. 6a as gray-shaded areas). Events are labeled throughout the 24-h data, including neck motions as performed per the protocol mentioned above as well as additional events including extubation, vocalizations, PT sessions, and walking. These isolated events are shown in subplots in Figure 6b. While neck motions were analyzed and characterized in detail (see online suppl. Appendix D), these other additional events also produced visually distinct motion signatures. Extubation and vocalization produced discrete and visually distinct waveforms. PT and walking produced more continuous waveforms. The cyclical pattern of the PT waveform mirrors that of the controlled neck motions which is as expected as the PT sessions involved performing neck motions (rotation, flexion, extension) that were performed in the controlled data collection sessions. Walking, a more variable motion, expectedly produced a noisier, less uniform waveform. Heart rate (HR) and respiratory rate (RR) were computed for the 24-h period using a previously validated

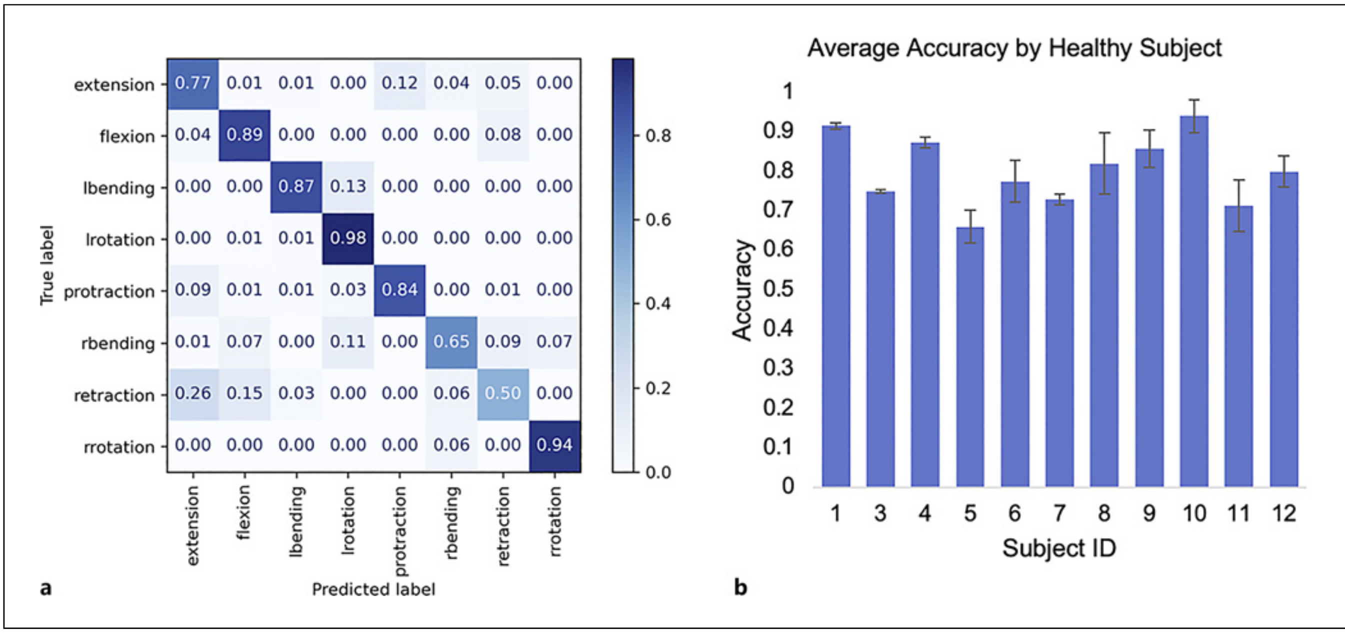

Fig. 4. **a** Averaged confusion matrix from ten iterations of leave-one-subject-out cross validation on healthy normal data set. **b** Average classification accuracy by each healthy normal subject. Mean classification accuracy of 80% was obtained across 11 healthy normal subjects that were analyzed.

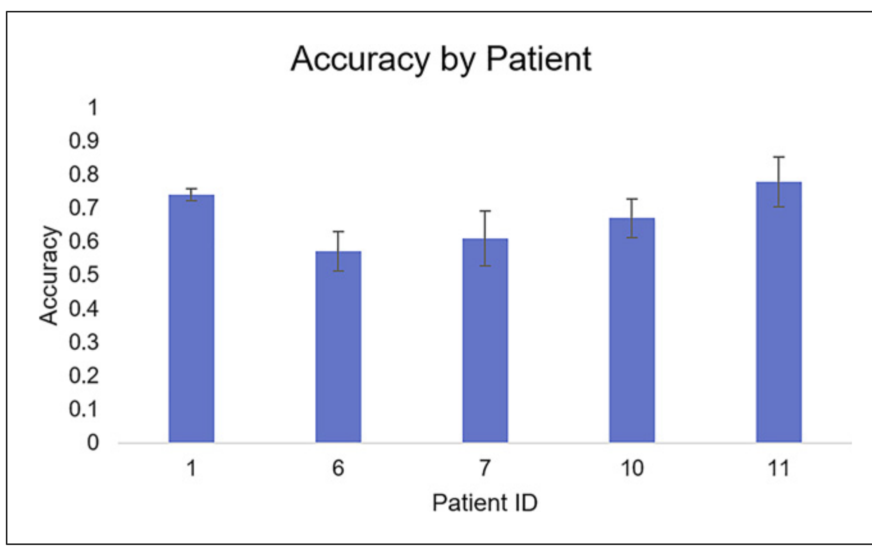

Fig. 5. Average classification accuracy by each patient. Mean classification accuracy of 67.5% was obtained across 5 patients that were analyzed.

algorithm. A portion of the HR and RR during a period of sleep is shown in Figure 6b R. Within this period of sleep, the z-component of linear acceleration clearly shows the periodic HR tracing with two distinct waveforms corresponding to S1 and S2 heart sounds.

Discussion

In this pilot study, we have demonstrated a novel application of ADAM for monitoring CROM in the immediate (24-h) postoperative period in the cervical

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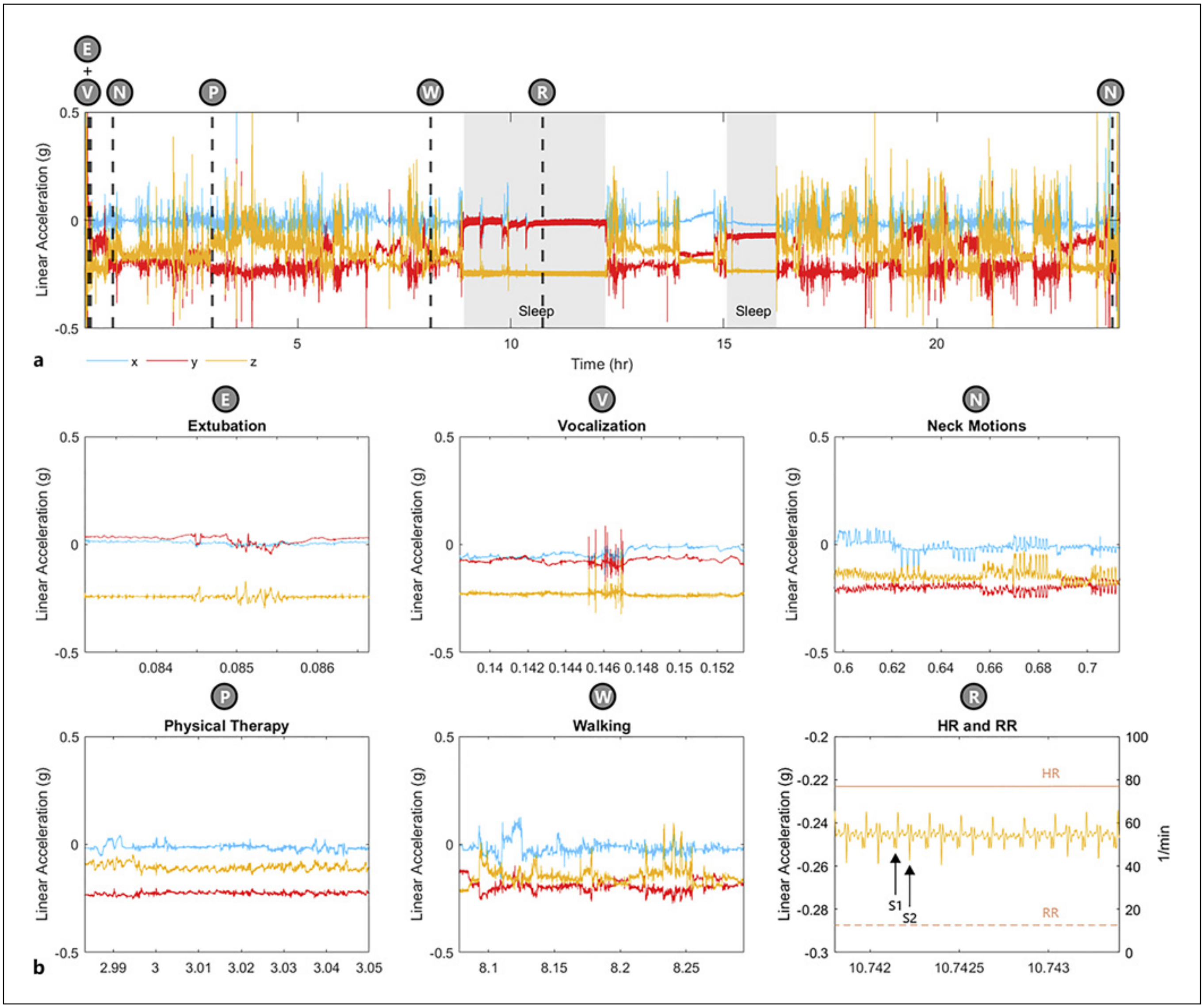

Fig. 6. **a** Continuous 24-h data collection for a postoperative ACDF patient, capturing various events. **b** Motion signatures of captured events, including extubation (E), vocalizations (V), neck motions (N) during ROM protocol, PT (P), walking (W), and continuous HR and RR monitoring (R).

spine patient population, specifically patients who have undergone ACDF. ADAM can measure multiple metrics in the postoperative course related to functionality, safety, and overall recovery progress (e.g., adherence to PT or neck motion restrictions, regaining of CROM).

This study focuses on validating, in a limited patient population, the ability of ADAM to differentiate between eight unique neck motions (right and left rotation, right and left lateral bending, flexion, extension, retraction, protraction) in the three cardinal planes that make up the neck movements of daily activity. Sensor data of neck motions in healthy normal subjects and patients reveal unique motion signatures (online suppl. Appendix D) that formed the basis for training a machine learning classification algorithm. Cross validation of our algorithm on our data set obtained from healthy normal individuals demonstrated a classification accuracy of 80%. Given the variability within our data set, including in the speed and magnitude of motions seen across the spectrum of healthy to postoperative patients, our current algorithm is robust in handling these differences while maintaining high classification accuracy. While the current classification algorithm was validated using data collected in a controlled setting, one goal is to ultimately apply the algorithm more widely to additional settings, such as ambulatory care and the home setting. With approaches such as noise filtering or further training with noisier samples, this algorithm can be used to measure neck motions in not only the immediate postoperative period, as was done in this study, but also during supervised PT sessions and at home to monitor adherence to neck exercises after hospital discharge. Monitoring of neck motions in these settings could confirm that beneficial neck motions (e.g., rotation, flexion, extension, retraction) are performed and potentially deleterious neck motions (e.g., protraction) are avoided. After further refining our algorithm's ability to measure magnitudes of neck motions, our algorithm can also feasibly monitor the progression and regaining of CROM after ACDF and the effect of rehabilitation.

In addition to neck motion monitoring, the additional events that were qualitatively analyzed in this study (e.g., extubation, vocalizations, walking, as shown in Fig. 6) capture potential metrics that could be incorporated into our algorithm to offer more holistic monitoring of postoperative patients. In fact, these events demonstrate unique features that either have already or could form the basis of other classification algorithms. For example, a machine learning algorithm has been validated to detect and differentiate between coughing, speech, throat clearing, laughing, and motion artifact in COVID-19 patients [26], which can reasonably be applied to our data to detect these events. ADAM has also been internally validated to monitor other metrics such as vital signs (including HR and RR), swallow count, talking time, energy expenditure, and body and limb orientation. Swallow count and talking time can offer useful information in the assessment of dysphagia and dysphonia, common postoperative complications after ACDF [28, 29]. Vital signs, energy expenditure, and body orientation also provide metrics on overall functionality.

ADAM has received positive feedback from patients and physicians on their comfort, ease of use, and application in both short- and long-term studies. With its straightforward interrogation and data download process that can be controlled by patients through an iPad user interface, ADAM has been deployed successfully in several home studies already, further lending to its feasibility as a monitoring tool for in-hospital and at-home use.

There are important limitations in this pilot study. Regarding algorithm performance, there were specific neck motions that were difficult to classify, leading to relatively lower accuracies. Of the eight neck motions, right bending and retraction had the most variable motion signatures and lowest classification accuracies. Future efforts may include new mounting locations that are more specific to neck motion (e.g., forehead, chin) but less specific for parameters such as HR, RR, and swallowing. In exchange for this added functionality of measuring other important metrics, we may have limited our accuracy in classifying some neck motions. Normal variation in body habitus and clinical environment (e.g., hospital bed at variable incline, variable body orientation) likely limited classification accuracy as well. While ADAM is capable of measuring body orientation, this feature is not yet incorporated into our current classification algorithm to correct for varying body orientations, although this is a focus of future work. Another limitation of our study was that the ages of healthy normal subjects and patients were not age-matched due to availability of subjects. Future studies would ideally recruit a larger number of participants of varied ages to allow for age-matching. Regarding algorithm practicality, our algorithm was limited to classifying 4-s samples of neck motion without any extraneous noise-introducing activities (e.g., walking, talking). To be practical in the clinical setting, our algorithm needs to be modified to recognize neck motions of varying length/speed and with superimposed extraneous activity. Incorporation of prior algorithms developed to detect walking and speech ideally would allow for high-fidelity neck motion classification despite other ongoing activity that frequently occurs in the hospital or home setting. Further training to quantitate magnitude of motion would also be beneficial. Additionally, our pilot study focuses only on isolated neck motions in a single plane, which does not reflect compound movements that occur in real life. While our algorithm is well equipped to monitor isolated neck motion exercises in PT, further algorithm development is needed to track more complex neck movements of daily activity. Lastly, our algorithm assumed all movement occurred solely at the cervical level when classifying neck motions, despite possible minor movement of the thoracic spine even in our controlled setting. Therefore, the algorithm would need to be improved to detect other motions irrelevant to neck movement to differentiate them from movement restricted to the cervical spine.

This pilot study demonstrates the ability of ADAM to be acceptable to both surgeons and patients in a real-world clinical setting after cervical spine surgery. ADAM was able to measure CROM, demonstrating a new frontier in postsurgical patient monitoring despite limitations of our study. Additional patient enrollment will shape robust data sets and allow for continual algorithmic improvement as well as the expansion of the clinical scenarios in which remote postsurgical patient monitoring can be enhanced.

Statement of Ethics

Study procedures were approved by the Northwestern University Institutional Review Board (STU00213413) and registered on ClinicalTrials.gov (NCT04921800). All participants (N = 19), both healthy normal subjects (n = 14) and patients (n = 5), provided written consent prior to participation in this research study. Written informed consent was obtained from the patients for publication of the details of their medical case and any accompanying images.

Conflict of Interest Statement

S.X., K.S.C., L.Y., and J.Y.L. are employees of a small private company with commercial interest in the technology. S.X. reports equity ownership in a small private company with a commercial interest in the technology. J.Y.L., H.J., and S.X. report inventorships and potential royalties in patents assigned to Northwestern University. A.A.P. has no relationship directly or indirectly related to the topic of investigation. He has the following, unrelated conflicts of interest: consulting: Zimmer Biomet, DePuy Synthes, nView, CTL Amedica, Kuros Biosciences, Alphatec Spine; product design/royalties: Nuvasive, CTL Amedica, Alphatec Spine; stock options/ownership (<1%): Aclarion, Cytonics, Tissue Differentiation Intelligence, Endoluxe, nView; institutional fellowship program support: NuVasive, AO Spine North America; board of directors (nonfinancial): Cervical Spine Research Society; Editorial Board: Contemporary Spine Surgery, Journal of the American Academy of Orthopaedic Surgery (Deputy Editor).

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Author Contributions

L.H., A.A.P., and S.X. designed the research. L.H., A.S., J.B., A.A.P., and S.X. performed research, with help from J.Y.L. and K.M. L.H., K.S.C., L.Y., A.S., and H.C. analyzed data, with help from Y.K. and H.J. L.H., K.S.C., and S.X. wrote the manuscript.

Data Availability Statement

All relevant data are included in the article. Additional supporting data are available from the corresponding author on request. All requests for raw and analyzed data and materials will be reviewed by the corresponding author to verify whether the request is subject to any intellectual property or confidentiality obligations.

References

1 Fejer R, Kyvik KO, Hartvigsen J. The prevalence of neck pain in the world population: a systematic critical review of the literature. Eur Spine J. 2006;15(6):834–48.
2 Murray CJL, Atkinson C, Bhalla K, Birbeck G, Burstein R, Chou D, et al. The state of US health, 1990-2010: burden of diseases, injuries, and risk factors. JAMA. 2013;310(6):591–608.
3 Hoy D, March L, Woolf A, Blyth F, Brooks P, Smith E, et al. The global burden of neck pain: estimates from the global burden of disease 2010 study. Ann Rheum Dis. 2014;73(7):1309–15.
4 Safiri S, Kolahi A-A, Hoy D, Buchbinder R, Mansournia MA, Bettampadi D, et al. Global, regional, and national burden of neck pain in the general population, 1990-2017: systematic analysis of the Global Burden of Disease Study 2017. BMJ. 2020;368:m791.
5 Borghouts JAJ, Koes BW, Vondeling H, Bouter LM. Cost-of-illness of neck pain in The Netherlands in 1996. Pain. 1999;80(3):629–36.
6 Cohen SP. Epidemiology, diagnosis, and treatment of neck pain. Mayo Clin Proc. 2015;90(2):284–99.
7 Mochida K, Komori H, Okawa A, Muneta T, Haro H, Shinomiya K. Regression of cervical disc herniation observed on magnetic resonance images. Spine. 1998;23(9):990–7; discussion 996-7.
8 Bible JE, Kang JD. Anterior cervical discectomy and fusion: surgical indications and outcomes. Semin Spine Surg. 2016;28(2):80–3.
9 Fehlings MG, Wilson JR, Yoon ST, Rhee JM, Shamji MF, Lawrence BD. Symptomatic progression of cervical myelopathy and the role of nonsurgical management: a consensus statement. Spine. 2013;38(22 Suppl 1):S19–20.
10 Song KJ, Choi BY. Current concepts of anterior cervical discectomy and fusion: a review of literature. Asian Spine J. 2014;8(4):531–9.
11 Epstein NE. A review of complication rates for anterior cervical diskectomy and fusion (ACDF). Surg Neurol Int. 2019;10(100):100.
12 Wu XD, Yuan W, Chen HJ, Chen Y, Wang JX, Cao P, et al. Neck motion following multilevel anterior cervical fusion: comparison of short-term and midterm results. J Neurosurg Spine. 2013;18(4):362–6.
13 Tommasi DG, Foppiani AC, Galante D, Lovecchio N, Sforza C. Active head and cervical range of motion: effect of age in healthy females. Spine. 2009;34(18):1910–6.
14 Roozmon P, Gracovetsky SA, Gouw GJ, Newman N. Examining motion in the cervical spine. II: characterization of coupled joint motion using an opto-electronic device to track skin markers. J Biomed Eng. 1993;15(1):13–22.
15 Bergman GJD, Knoester B, Assink N, Dijkstra PU, Winters JC. Variation in the cervical range of motion over time measured by the “flock of birds” electromagnetic tracking system. Spine. 2005;30(6):650–4.
16 Dall’Alba PT, Sterling MM, Treleaven JM, Edwards SL, Jull GA. Cervical range of motion discriminates between asymptomatic persons and those with whiplash. Spine. 2001;26(19):2090–4.

17 Wang SF, Teng CC, Lin KH. Measurement of cervical range of motion pattern during cyclic neck movement by an ultrasound-based motion system. Man Ther. 2005;10(1):68–72.
18 Feipel V, Rondelet B, Le Pallec JP, Rooze M. Normal global motion of the cervical spine: an electrogoniometric study. Clin Biomech. 1999;14(7):462–70.
19 Bible JE, Biswas D, Miller CP, Whang PG, Grauer JN. Normal functional range of motion of the cervical spine during 15 activities of daily living. J Spinal Disord Tech. 2010; 23(1):15–21.
20 Maselli M, Mussi E, Cecchi F, Manti M, Tropea P, Laschi C. A wearable sensing device for monitoring single planes neck movements: assessment of its performance. IEEE Sens J. 2018;18(15):6327–36.
21 Lee K, Ni X, Lee JY, Arafa H, Pe DJ, Xu S, et al. Mechano-acoustic sensing of physiological processes and body motions via a soft wireless device placed at the suprasternal notch. Nat Biomed Eng. 2020;4(2):148–58.
22 O'Brien MK, Botonis OK, Larkin E, Carpenter J, Martin-Harris B, Maronati R, et al. Advanced machine learning tools to monitor biomarkers of dysphagia: a wearable sensor proof-of-concept study. Digit Biomark. 2021; 5(2):167–75.
23 Chun KS, Kang YJ, Lee JY, Nguyen M, Lee B, Lee R, et al. A skin-conformable wireless sensor to objectively quantify symptoms of pruritus. Sci Adv. 2021;7(18):eabf9405.
24 Yang AF, Chun KS, Yu L, Walter JR, Kim D, Lee JY, et al. Validation of a hand-mounted wearable sensor for scratching movements in adults with atopic dermatitis. J Am Acad Dermatol. 2023;88(3):726–9.
25 Jeong H, Lee JY, Lee K, Kang YJ, Kim JT, Avila R, et al. Differential cardiopulmonary monitoring system for artifact-canceled physiological tracking of athletes, workers, and COVID-19 patients. Sci Adv. 2021;7(20): eabg3092.
26 Ni X, Ouyang W, Jeong H, Kim J-T, Tzaveils A, Mirzazadeh A, et al. Automated, multiparametric monitoring of respiratory biomarkers and vital signs in clinical and home settings for COVID-19 patients. Proc Natl Acad Sci USA. 2021;118(19): e2026610118.
27 Lonini L, Shawen N, Botonis O, Fanton M, Jayaraman C, Mummidisetty CK, et al. Rapid screening of physiological changes associated with COVID-19 using soft-wearables and structured activities: a pilot study. IEEE J Transl Eng Health Med. 2021;9:4900311.
28 Rosenthal BD, Nair R, Hsu WK, Patel AA, Savage JW. Dysphagia and dysphonia assessment tools after anterior cervical spine surgery. Clin Spine Surg. 2016;29(9):363–7.
29 Rosenthal BD, McCarthy MH, Bhatt S, Savage JW, Singh K, Hsu WK, et al. A comparison of patient-centered outcome measures to evaluate dysphagia and dysphonia after anterior cervical discectomy and fusion. J Am Acad Orthop Surg. 2019;27(22): 848–53.