

Wearable Sensing for Postural Monitoring and Spinal Health: A Concise Review

Jialing Ma^{1#}, Guangrong Zhang^{1#}, Yingji Fu¹, Qilong Jin², Yaling Gao³

¹ School of Pharmacy, Ningxia Medical University, Yinchuan 750004, Ningxia, China

² School of Traditional Chinese Medicine, Ningxia Medical University, Yinchuan 750004, Ningxia, China

³ The Third Clinical Medical College, Ningxia Medical University, Yinchuan 750004, Ningxia, China

Jialing Ma and Guangrong Zhang contributed equally to this work.

Abstract: In recent years, wearable sensors have opened the door to posture tracking outside the clinic. Inertial measurement units (IMUs), often combined with pressure, electromyographic, or flexible strain sensors, provide continuous information about body position and the effort of the muscles that hold it. Machine learning turns these raw signals into recognizable activity and posture states, and real-time feedback can prompt users to correct themselves as they go about daily life. This review brings together recent work on multimodal sensing, human activity recognition, and closed-loop intervention, with particular attention to spinal health. We also look closely at the obstacles that keep recurring in the literature: sensors drift and shift on the body, algorithms trained on one group of users often fail on another, and there is still no shared definition of what counts as an abnormal posture. Feedback fatigue, the tendency to ignore alerts after continued exposure, further limits long-term acceptance. We argue that progress will depend on personalized calibration, feedback that adapts to the individual user, and assessment that reaches beyond short experiments. In our view, wearable posture devices are moving toward integrated spinal health management rather than serving as simple reminders.

Keywords: wearable sensors; posture monitoring; IMU; multimodal fusion; activity recognition; intelligent feedback; spinal health

1. Introduction

Prolonged sitting and heavy use of smartphones and computers have made poor posture a growing concern. Traditional assessment methods, whether visual inspection, imaging, or motion capture in a laboratory, can only provide snapshots of behavior and cannot follow people through a normal day. Wearable IMUs help to close this gap by recording continuous kinematic data, and they can be paired with pressure, surface electromyography (sEMG), or flexible sensors that reveal how load is distributed and how muscles are working. Machine learning then converts these signals into posture classifications, and real-time feedback completes a loop in which monitoring, recognition, and correction reinforce one another [1-3]. In this review we focus on wearable technologies for posture monitoring and spinal health intervention. Our discussion centers on multimodal sensing, algorithmic recognition, feedback strategies, and the limitations that remain.

2. Multimodal Wearable Sensing

A typical IMU contains a triaxial accelerometer and a gyroscope, with a magnetometer sometimes added on top. Accelerometers give reliable estimates of inclination while the body is nearly stationary; gyroscopes record angular velocity but accumulate drift over time, which is why fusion algorithms such as complementary or Kalman filters are almost always involved [4]. The meaning of the data also depends on where the sensor is worn. A head-mounted unit mainly picks up forward head posture, a collar sensor reflects motion of the upper trunk, and a waist sensor characterizes the overall activity of the torso. Modular designs add flexibility but create new demands: each module must be able to recognize its own orientation automatically, and calibration has to be individualized rather than reduced to fixed angle thresholds.

Pressure sensors can detect asymmetrical loading while a person sits, although most of the evidence so far comes from laboratory settings rather than free-living use [5]. sEMG offers a window into the muscle activity that sustains posture and therefore complements the kinematic picture [6]. Flexible strain gauges and textile-based sensors conform well to the body, yet they are plagued by hysteresis, limited repeatability, and calibration difficulties [7]. Signals from different modalities can be fused at the data, feature, or decision level. For lightweight devices, feature-level fusion seems the most practical route, for example combining posture angles with pressure asymmetry and center-of-pressure indices [8]. Still, adding more sensors does not automatically improve accuracy; when synchronization, fixation, or redundant information becomes the

dominant problem, multimodality can actually hurt performance.

3. Posture Recognition and Intelligent Feedback

Early systems worked with simple thresholds. They were easy to implement but could not tell a transient movement from a sustained poor posture. Machine learning and deep learning models, from support vector machines and random forests to CNNs and LSTMs, classify posture with greater accuracy, yet their performance tends to drop when they meet new users or new environments [9]. A hierarchical approach appears more sensible. The system would first determine the activity context, then judge how far the posture deviates from expectation, and only then combine duration with the individual baseline before deciding whether feedback is warranted. That last step matters because the same angle can carry very different meaning for different people, and personal calibration is therefore essential.

Real-time vibrotactile feedback disturbs users less than auditory or visual cues and is generally acceptable in classrooms and offices [1,10]. Frequent alerts, however, quickly exhaust patience, a problem commonly described as feedback fatigue. One way to keep reminders meaningful is to trigger them only when both the size and the duration of a deviation exceed a threshold, so that a brief forward lean does not set off the device. Recording how the user responds and adjusting the reminder frequency accordingly also seems worthwhile. Wearables can go beyond reminders altogether. Some systems now prescribe active exercises, such as neck-shoulder stabilization or trunk control, while the IMU monitors the quality of movement during the session [11]. Gamified training offers another way to sustain motivation, but the game must remain aligned with therapeutic goals and must not reward compensatory movements [12].

4. Challenges and Future Directions

A set of problems keeps reappearing across studies. Sensors drift and are not always fixed firmly to the body; wearing positions vary between users and even between sessions; and researchers have yet to agree on a common definition of abnormal posture. Algorithms that work well for one population often generalize poorly to another. Feedback fatigue erodes long-term acceptance, and clinical evidence for adolescent spinal health in particular is still sparse [2,13]. We would also caution against conflating different levels of claims. Recognizing a posture is not the same as diagnosing a disease, improving behavior is not the same as correcting a structural problem, and a short-term response to feedback is not proof of a long-term health benefit.

Looking ahead, several priorities stand out. Multimodality has to be weighed against the practical constraints of lightweight, comfortable devices. Personalized models built on individual baselines will probably outperform generic ones, and closed-loop intervention should be linked to active exercise and to longitudinal assessment, possibly through cloud-based platforms. Above all, the field needs long-term studies in real-world settings that connect engineering metrics with actual behavioral change and health outcomes.

5. Conclusion

Wearable IMUs and multimodal sensors, together with machine learning and real-time feedback, have made continuous posture monitoring and behavioral intervention feasible outside the clinic. The technology is still held back by sensor variability, limited generalization of algorithms, and the tendency of users to tire of reminders. Future development should concentrate on personalization, closed-loop intervention, and long-term digital management. Only along this path can wearable posture devices grow beyond simple reminders and become platforms that measurably support spinal health.

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