Wearable sensing

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Wearables that learn to read gestures on the move

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A wearable sensing system that learns from motion artifacts enables reliable gesture control during movement.

A wearable sensing system that operates only when the body is still is not practical; it functions more as a laboratory instrument. For decades, research in human–machine interfaces (HMIs) has treated motion artifacts as disturbances to be eliminated rather than as engineering conditions to be understood. Once the body moves – through running, vibration, or posture shifts – sensor signals distort, gestures dissolve into artifacts, and the interface loses its ability to reliably connect human intention with machine response.

Writing in *Nature Sensors*, Chen and colleagues present a deep-learning-enhanced wearable interface that remains robust under motion artifacts[1]. Their work reframes such artifacts not as contaminants to be filtered out but as learnable structures – features of empirical data that can be modelled and predicted (Fig. 1). The fragility of wearable sensing under motion has long prevented it from being translated beyond the lab. The authors tackle this challenge not with hardware stabilization, but by training the system to interpret motion directly. This approach marks a broader shift in the field: robustness in wearable sensing now arises not from isolating devices from their surroundings but from training systems to interpret them. Recent AI-driven platforms, from stress-responsive electronic skins[2] to motion-adaptive ultrasound wearables[3], exemplify this turn toward learning from complex, real-world signals. In HMIs, motion artifacts are integrated into the training distribution instead of being regarded as noise.

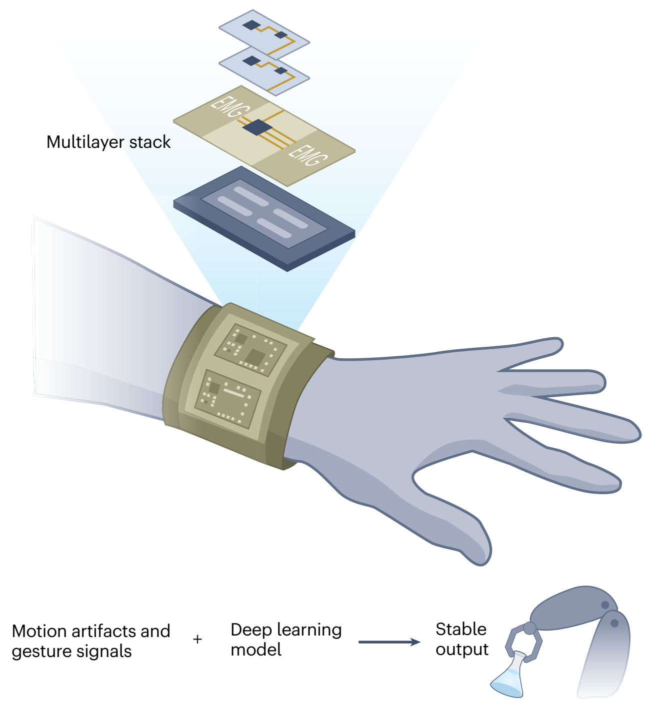

Fig. 1 | Motion-tolerant wearable human–machine interface. The wearable patch integrates an IMU, EMG amplifier, and wireless MCU to record gestures while the user moves. Composite signals, including both gesture data and motion artifacts, are fed into a deep-learning model that robustly decodes intended movements.

Traditional strategies for addressing motion artifacts have followed two dominant paths. One is mechanical and materials-based – stiffening mounts, isolating sensors, or fabricating auxiliary channels to subtract drift[4]. The other is algorithmic – masking spectral bands, smoothing waveforms, or subtracting structured interference. Both treat motion as an external noise to be removed. This assumption can be inverted: rather than reconstructing an ideal 'clean' gesture, the system is trained to perceive gestures through the artifacts. The composite dataset comprised 46,930 segmented signals per subject across 19 gesture types, generated by superimposing clean gesture traces with motion artifacts from running, vibration, posture change, and simulated wave motion. The neural network learns not to reject these samples but to recognize gesture as an invariant pattern embedded within them.

The system deploys a multilayer wearable patch integrating a six-channel inertial measurement unit (IMU) for accelerometry and gyroscopy and an electromyography (EMG) channel for grasping intent. A convolutional neural network (CNN) processes IMU signals using the composite dataset, enabling real-time gesture recognition during running and other disturbances. EMG signals, which resist inertial interference but can drift, are filtered to infer grasp execution. Together, these channels identify both the category of intended motion and its timing. Demonstrations show a user controlling a robotic arm while running, with the system maintaining stable motion despite heavy artifacts. The full control loop exhibited a latency of ~1.3 s (including ~1 ms CNN inference time), yet produced smooth, intention-aligned actuation even under continuous motion.

This work reflects a broader shift in wearable sensing – from suppressing variability to learning from it. The same principle underlies recent advances across the field: AI-enabled sweat diagnostics[2], ultrasound systems that track rather than resist motion[3], electronic skins that maintain readout under deformation[5], and adaptive classifiers that learn in situ[6]. In parallel, neuromuscular decoding at the edge increasingly fuses IMU, EMG, and strain signals to infer gestures during motion[7]. Collectively, these developments suggest that 'robust in motion' is transitioning from a research aspiration to a baseline expectation.

The platform also addresses a critical translational barrier: it operates without environmental or behavioural constraints. That distinction separates a proof-of-principle from a deployable class. The system employs parameter-based transfer learning, fine-tuned with data from six users; remarkably, it required only two samples per gesture from a new user to reach over 92% recognition accuracy — a substantial improvement from ~51% before transfer, eliminating the need for full retraining. Its sliding-window inference supports continuous operation, though the current one-second window is still suboptimal for latency-critical contexts such as surgical teleoperation or augmented-reality feedback. The system filters EMG signals through conventional methods and analyses IMU data with the deep model; integrating these modalities during training could enable higher-dexterity prosthetic and robotic control under unconstrained motion.

Rather than suppressing motion artifacts, the challenge now is to train systems to interpret real-world signals across users and contexts, making composite dataset design, transfer learning, and cross-modal integration central to progress.

Parallel advances reinforce this direction. Researchers now view the management of motion artifacts in wearable platforms as an algorithmic issue[6]; adaptive biosensing treats nuisance variation as structure[7]; motion-tolerant ultrasound applies learning not to remove interference but to stabilize targets through it[3]; and AI-assisted soft electronics are converging toward inference-first architectures that no longer assume stillness as a precondition[4,8]. In that light, the authors' contribution is not only technical but conceptual: it marks a shift toward wearable sensing systems that function by engaging with their environment rather than withdrawing from it.

By reversing the logic of noise handling and demonstrating stability at the level of action, the authors offer a credible template for motion-operable interfaces. Future efforts could extend this strategy to underwater communication, sports rehabilitation, or assistive robotics for individuals with tremor or spasticity, where motion artifacts are intrinsic rather than avoidable. Integrating multimodal sensing streams such as ultrasound, bioimpedance, or vision could further test the scalability of artifact-aware learning across sensing domains. As wearable technologies expand to respiratory monitoring[9], electronic skins[2,6], neurological systems[2], and mental-state inference[10], operation under realistic motion will become a baseline expectation for wearable devices. The conceptual inflection is decisive: the real environment is no longer the enemy of the signal — it becomes part of the training set.

The implications are far-reaching. If motion artifacts are no longer a reason to discard data, the operational scope of wearable sensing and HMIs extends far beyond controlled laboratories into the unstructured settings where people actually move — streets, vehicles, factories, even aquatic environments. This advance does not depend on vibration-proof hardware or mechanically stabilized sensors, but on training models to interpret signals as they naturally occur. The key contribution lies not merely in preserving gesture-classification accuracy under artifact load, but in maintaining downstream signal fidelity precisely when conventional systems fail. The issue is resolved at the level that ultimately matters: embodied action.

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References

1. Chen, X. et al. *Nat. Sens.* https://doi.org/10.1038/s44460-025-00001-3 (2025).
2. Xu, C. et al. *Nat. Electron.* **7**, 168–179 (2024).
3. Lin, M. et al. *Nat. Biotechnol.* **42**, 448–457 (2024).
4. Zhao, C. et al. *Nat. Electron.* **8**, 981–993 (2025).
5. Huang, Z. et al. *Nat. Electron.* **1**, 473–480 (2018).
6. Yin, J. et al. *Nat. Rev. Bioeng.* **2**, 541–558 (2024).
7. Moin, A. et al. *Nat. Electron.* **4**, 54–63 (2021).
8. Gao, X. et al. *Nat. Electron.* **7**, 1035–1046 (2024).
9. Kim, J.-H. et al. *Nat. Electron.* **5**, 794–807 (2022).
10. Ates, H. C. et al. *Nat. Rev. Mater.* **7**, 887–907 (2022).

Competing interests

The authors declare no competing interests.