

A wireless magnetic implant system for continuous neuromuscular sensing

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Precise measurement of neuromuscular mechanics provides an intuitive control signal for synchronizing movement with wearable robotics. However, obtaining such measurements remains challenging, as current muscle-sensing technologies require substantial trade-offs among signal fidelity, system complexity and invasiveness. Here we present a skin-mounted magnetometer array platform that wirelessly tracks passive 3-mm-diameter magnetic beads implanted within human muscle tissue for continuous neuromuscular sensing. The system integrates customized high-density sensing electronics with an information-theoretic architecture, enabling sub-millimetre resolution of real-time muscle dynamics at depths of up to 6 cm. We deployed the platform in three participants with transtibial amputation, tracking a constellation of permanently implanted magnets to support neuroprosthetic control with multiple degrees of freedom. Wireless muscle-state estimation matched or outperformed standard surface and implanted electromyography across most evaluated outcomes, achieving accurate and responsive neuroprosthetic movement in these participants. We further demonstrate muscle activation detection through magnetic induction alone, highlighting a potential alternative to electromyography.

Scientists, technologists and clinicians have long sought neural interfaces that enable reproducible and repeatable signalling between the peripheral nervous system and wearable robotics designed to restore lost biological capabilities^{1–3}. Electromyography (EMG), whereby electrodes record muscle electrical activity to infer user intent, has been the predominant approach for neuroprosthetic control^{4,5}. Despite considerable research focused on enabling more versatile, direct neural control of movements, widespread clinical adoption has remained elusive due to several limitations^{6,7}. EMG monitors electrical rather than

mechanical signals, requiring complex models and continual calibration to infer muscle state or force^{8–10}. Additionally, current surface EMG (sEMG) sensing platforms suffer from electrode–skin liftoff, movement artefacts and changes in skin impedance that limit performance outside controlled laboratory environments^{11,12}. Implanted EMG (iEMG) mitigates these performance shortcomings, but introduces its own considerations: fine-wire systems carry chronic infection risk from percutaneous connections, whereas fully wireless systems require implanted electronics for signal transmission and power coupling,

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resulting in larger implants and additional failure modes^{13–17}. Recent bionic limb work indicates that deeper physical integration with the body may be necessary to recover versatile movements, and research focusing on new surgical techniques, powered prostheses and neural control requires a viable and efficacious mechanoneural sensing interface^{1,3,17–21}.

Sensing directly in the mechanical domain offers more interpretable and physiologically aligned access to tissue dynamics^{22,23}. Sonomicrometry and fluoromicrometry can measure muscle dynamics^{24–26}, but sonomicrometry requires highly invasive tethered implants, fluoromicrometry involves radiation exposure and neither technique is fully portable. Ultrasound is actively being explored as a real-time sensing interface, with work ongoing to improve transducer portability^{27–30}. B-mode ultrasound tracking requires substantial signal processing and bulky probes that limit deployable wearability^{30,31}. A-mode approaches, while showing promise for neuroprosthetic applications, rely on trained models to map ultrasound features to joint kinematics or predefined movements, rather than providing direct muscle length and speed measurements^{30,32}.

Muscle magnetic-based measurement techniques based on implanted magnets and external sensing arrays have been evaluated in both preclinical animal models^{33–35} and humans^{36,37}. In preclinical studies, magnet tracking achieves high signal-to-noise ratios (SNRs) but only at shallow tracking depths (~3 cm), further limiting accessible muscle signals and neuroprosthetic functionality^{33,34}. Previous human studies have demonstrated the feasibility of implanted magnets for neuroprosthetic control. These interfaces rely on classification to decode a set of predetermined discrete movements; where direct and continuous control is achieved, limited signal independence restricts control to a single degree of freedom (DOF)³⁶. Other interfaces track magnetic field changes rather than computing magnet positions³⁷. For direct control, neither approach has yet shown a clear control performance advantage over sEMG, nor has either been evaluated against iEMG interfaces. Furthermore, previous work in humans involved substantially larger magnets³⁷ or short-term implantation³⁶. In summary, existing systems have yet to achieve the concurrent goals required for high-fidelity neuroprosthetic control, namely small implant size, low latency, precise localization, high SNR and deep multi-magnet tracking (Supplementary Table 1).

In this Article, we present a wearable, wireless muscle-state estimator (MuSE) that enables simultaneous tracking of multiple 3-mm-diameter magnetic beads implanted in muscle with sub-millimetre resolution at depths of up to 6 cm (Fig. 1a,b). To capture the full muscle state in humans, we designed custom electronics comprising a high-density magnetic field sensor architecture driven by a field-programmable gate array (FPGA) for high-bandwidth, parallel measurements. We formulated a computationally efficient localization algorithm based on information theory that exploits multiplexed sensing to decode precise magnet positions and velocities from measured field data. Continuous in vivo monitoring of muscle tissue dynamics is estimated from the magnet movement (Fig. 1c). To demonstrate the MuSE system's capabilities, we conducted an early feasibility study on three participants with transtibial amputation. Up to six magnets were implanted in four residual limb muscles to enable direct neuroprosthetic control. These same four muscles were also instrumented with both invasive and skin-mounted EMG electrodes. Through this augmented neuroprosthetic interface on our three study participants, the MuSE generates more interpretable and mechanically representative control signals compared with both surface and invasive EMG interfaces. During specific neuroprosthetic tasks performed by the participants, the MuSE interface could sustain stable and multi-DOF control that met or exceeded that of the EMG interfaces on a preponderance of evaluated outcomes. We further leveraged the principles of magnetic induction to enable muscle activation sensing through a compact auxiliary coil, demonstrating the potential for comprehensive muscle-state monitoring.

Wireless MuSE system design

The MuSE system integrates four core components: (1) an external high-density magnetometer array that measures the magnetic fields generated by magnetic implants; (2) passive magnetic implants placed within the muscle tissue; (3) embedded high-bandwidth state estimation that tracks the magnets' positions and velocities using physics-based models and algorithms; and (4) real-time computation that derives muscle dynamics from the magnet states for neuroprosthetic control (Fig. 1a–c). The external sensor array is a custom printed circuit board (PCB) comprising 640 three-axis magnetometers (LIS3MDL; STMicroelectronics) arranged on a rectangular 53 mm × 86 mm board (Fig. 1d). The PCB features sensors on both the top and bottom surfaces, with each surface containing a 20 × 16 grid (Methods and Supplementary Figs. 1 and 2). The magnetometers are calibrated using standard techniques to remove local magnetic biases and sensor-specific offsets, followed by an orientation calibration^{38,39} (Supplementary Note 1).

The implanted markers are spherical neodymium-based magnetic beads, approximately 3 mm in diameter (Fig. 1e,f). These passive implants require no power or electronics, allowing for permanent implantation without concerns for battery life or device failure. The surgical, foreign-body, coating and migration considerations common to any implant remain and motivate the bead's specific design. To promote long-term biocompatibility and stability, each bead is coated with a tri-layer system: a 10- to 25-μm Ni–Cu–Ni base; 5 μm of 99.9% pure gold; and a 21-μm Parylene C outer coating^{35,40–42}. This geometry, magnetic material and coating balance minimal tissue disruption with sufficient magnetic field strength for reliable tracking, as smaller beads would compromise signal quality whereas larger magnets would increase surgical invasiveness. In addition, we demonstrated the magnets' stability against migration and demagnetization in a magnetic resonance environment, enabling patients with these implants to receive magnetic resonance imaging up to 1.5 T⁴³. Furthermore, the MuSE system's magnetic beads are substantially smaller than magnets used in other work (Supplementary Table 1).

The system incorporates an FPGA computing module (Mercury XU5; Enclustra) that controls sensor sampling at 1 kHz and processes the multiplexed magnetic field data in real time. A custom carrier PCB connects the FPGA to the sensor array and provides communication interfaces for wireless or Ethernet data streaming to a neuroprosthetic interface (Fig. 1g). The MuSE system consumes approximately 11 W during continuous operation (Supplementary Fig. 3 and Supplementary Note 2). In this study, each board executed its own independent tracking algorithm within its local reference frame, but the MuSE design enables scalable deployment of multiple sensor arrays for expanded spatial coverage or increased tracking precision (Supplementary Figs. 4–11 and Supplementary Note 1).

Tracking characterization and spatial resolution

The MuSE system's high-density sensor array and high-throughput FPGA signal-processing architecture provide the electronic hardware foundation for precise multi-magnet tracking, but utilizing this capability requires a complementary algorithmic framework that can efficiently process the multiplexed sensor data in real time. Tracking multiple magnets implanted at varying depths across different muscles presents a substantial computational challenge. Traditional approaches using optimization methods such as the Levenberg–Marquardt algorithm solve the inverse dipole problem independently at each time step, which injects sensor noise directly into position estimates and becomes computationally expensive when tracking multiple magnets simultaneously^{39,44}. To address these limitations, we developed an information filter (INFO) framework that propagates uncertainty through precision matrices, explicitly models sensor noise characteristics and defines temporal correlations in magnet positions through second-order dynamics modelling (Fig. 2a, Supplementary Fig. 12 and Supplementary Note 3).

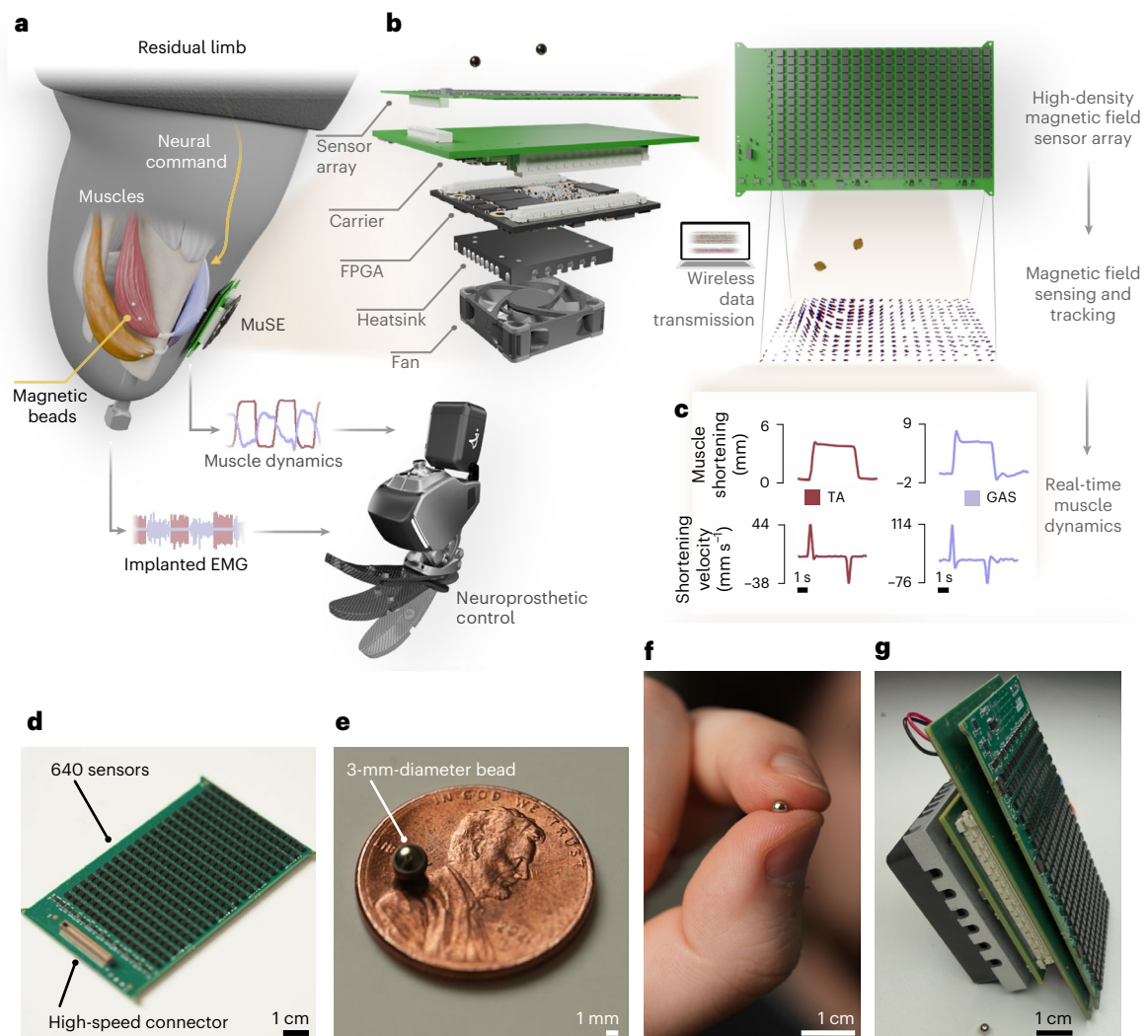


Fig. 1 | Wireless MuSE overview. **a**, Schematic and working principle of MuSE, whereby implanted magnets are placed in the residual muscles of an amputated limb to track muscle dynamics. The MuSE wirelessly provides measurements in real-time, encompassing the muscle state. These signals are used to infer joint dynamics for controlling either a robotic or virtual neuroprosthetic limb and are compared with standard or implanted muscle-sensing interfaces such as EMG. **b**, Illustration of the MuSE system. Embedded electronics comprise a 640-magnetic-field sensor board linked to an FPGA computing module through a custom carrier PCB that samples all 640 sensors at 1 kHz to track the magnets. The magnetic field information is then aggregated through a tracking algorithm that solves the inverse magnetostatics problem to map from the measured

fields to the magnet states. **c**, Measurement of the relative distance between two magnets within the same muscle belly enables the extraction of muscle tissue length and velocity (for example, in the GAS and tibialis anterior (TA) muscles). These muscle dynamic signals can be sent to a bionic prosthesis as neuromuscular control inputs. **d**, Photograph of a high-density sensor board that tracks the beads from outside the body. It is no larger than a credit card. **e,f**, Images of the small size (3 mm diameter) of the implanted magnetic beads without coating, with a penny for scale in **e**. **g**, Depiction of the entire embedded electronic system with all components, and a magnetic bead for scale. Credit: Image of the Mercury XU5 module courtesy of Enclustra.

We validated the tracking framework through both simulation and benchtop experiments. Simulation studies demonstrated that both INFO and Levenberg–Marquardt algorithms generally improved with increasing sensor density, showing reduced position error and variance as the sensor count increased (Fig. 2b). INFO consistently outperformed the Levenberg–Marquardt approach across all configurations, achieving lower mean position errors and reduced variance. The relationship between error and sensor count showed diminishing returns, consistent with spatial correlation among sensor measurements. For INFO, each sensor contributes additively to the information matrix. With the full number of sensors and at depths of 30–60 mm across different magnet positions, INFO maintained sub-millimetre tracking accuracy, whereas some Levenberg–Marquardt tracking errors exceeded 2 mm (Fig. 2c and Supplementary Fig. 13). The performance gap widened with depth, with INFO demonstrating significantly lower

errors and variance at all depths tested (Fig. 2c and Supplementary Fig. 14). Dynamic muscle simulation confirmed INFO's accurate tracking of physiological movements, achieving a substantially lower mean tracking error (0.42 versus 0.72 mm) and improved precision (0.38 versus 0.60 mm standard deviation) compared with the Levenberg–Marquardt approach (Fig. 2d).

Benchtop validation confirmed the advantages observed under simulation. INFO processing required 98 μ s per update at the 99th percentile compared with 5,530 μ s for the Levenberg–Marquardt approach, representing a speedup of more than 50-fold while simultaneously achieving lower estimation errors across all tested depths (Fig. 2e). The Levenberg–Marquardt method at depths beyond 30 mm began to exhibit mean millimetre-scale errors, whereas INFO maintained mean sub-millimetre errors (Supplementary Video 1). Although active cooling raises electromagnetic noise and lowers sensor SNR,

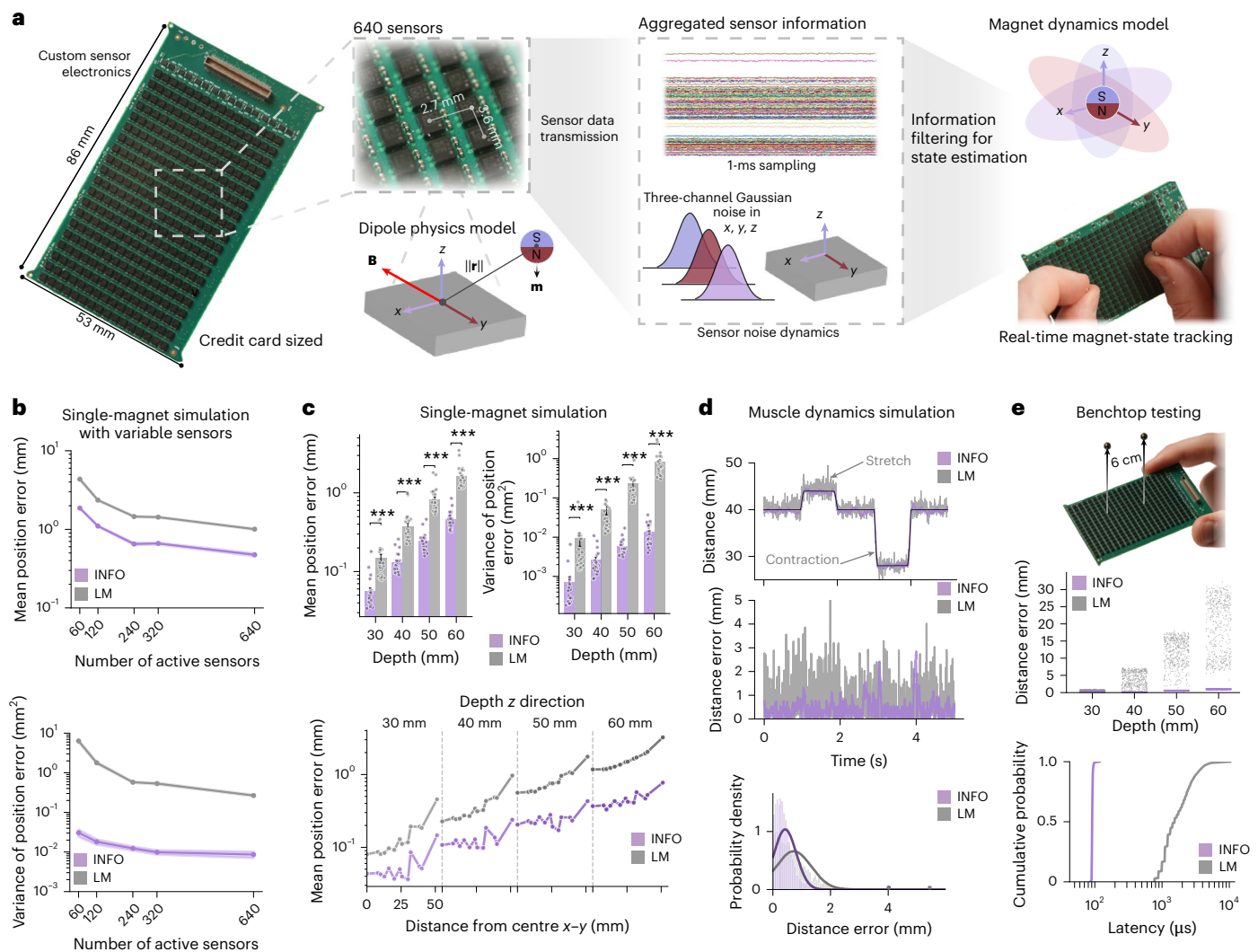


Fig. 2 | MuSE architecture with information theory. **a**, The information filter-based tracking algorithm (INFO) takes incoming aggregated sensor information and uses a dipole physics model to solve the inverse problem, computing the position and orientation of the magnetic bead. The tracking algorithm incorporated both sensor and magnet dynamics to reduce noise and variability in the estimation output. INFO was compared with the standard Levenberg–Marquardt (LM) optimization approach. **b**, Simulated test case to validate the impact of sensor number on estimating the magnet state ($n = 10$ independent trials per sensor number for each algorithm). **c**, Simulated test case involving the maximum number of sensors and a single static magnet at varying x , y and z positions. Comparisons of the estimation error and error variance between the two algorithms were made ($n = 26$ trials per depth for each algorithm; $n = 13$ positions, with $n = 2$

independent trials per position). For the mean position error comparisons, the P values were: $***P = 8.65 \times 10^{-8}$ at 30 mm, $***P = 1.46 \times 10^{-9}$ at 40 mm and $***P = 6.55 \times 10^{-10}$ for 50 and 60 mm. For the error variance comparisons, the P values were: $***P = 1.64 \times 10^{-8}$ at 30 mm and $***P = 6.55 \times 10^{-10}$ at 40–60 mm). **d**, Muscle dynamics simulation of both muscle stretch and contraction to evaluate each algorithm's capability to track realistic, fast dynamics at 5 cm depth. The distance reference for the two-magnet trajectory is overlaid with the outputs from the INFO and LM algorithms. The error across the trajectory time and its overall distribution are also shown. **e**, Benchtop results for both real-time algorithms tracking the distance between two static magnets at varying matched depths. Strip plots compare the distance error between the LM and INFO algorithms. Cumulative distribution plots depict algorithm latencies between INFO and LM. Statistical significance was determined by two-sided Mann–Whitney U test (Wilcoxon rank sum). The bars represent means and s.e.m. The shaded regions indicate s.e.m. for the line plots.

the tracking framework is more sensitive to thermal drift than to this interference, since INFO does not account for time-varying sensor bias (Supplementary Figs. 15 and 16). Real sensor noise dynamics exceeded our simulated model, widening the benchtop performance gap between algorithms. This formulation of the Levenberg–Marquardt approach treats each measurement step independently and cannot suppress time-varying noise, whereas INFO leverages state dynamics if the measurement uncertainty increases. Given that physiologically relevant muscle deflections occur at the millimetre scale, the errors and high variance in this formulation of the Levenberg–Marquardt approach would limit accurate muscle-state estimation,

and even more so if the magnets were exceedingly deep. This computational efficiency gain indicates that an improvement in the algorithm architecture need not compromise real-time tracking ability (Supplementary Video 2).

Demonstration of the MuSE system in humans

Having characterized the MuSE system's performance in tracking magnets, we determined its clinical feasibility in providing continuous muscle dynamics and then compared the signals with those of currently used sensing interfaces. We recruited three participants with transtibial amputations who had undergone a bionic reconstruction.

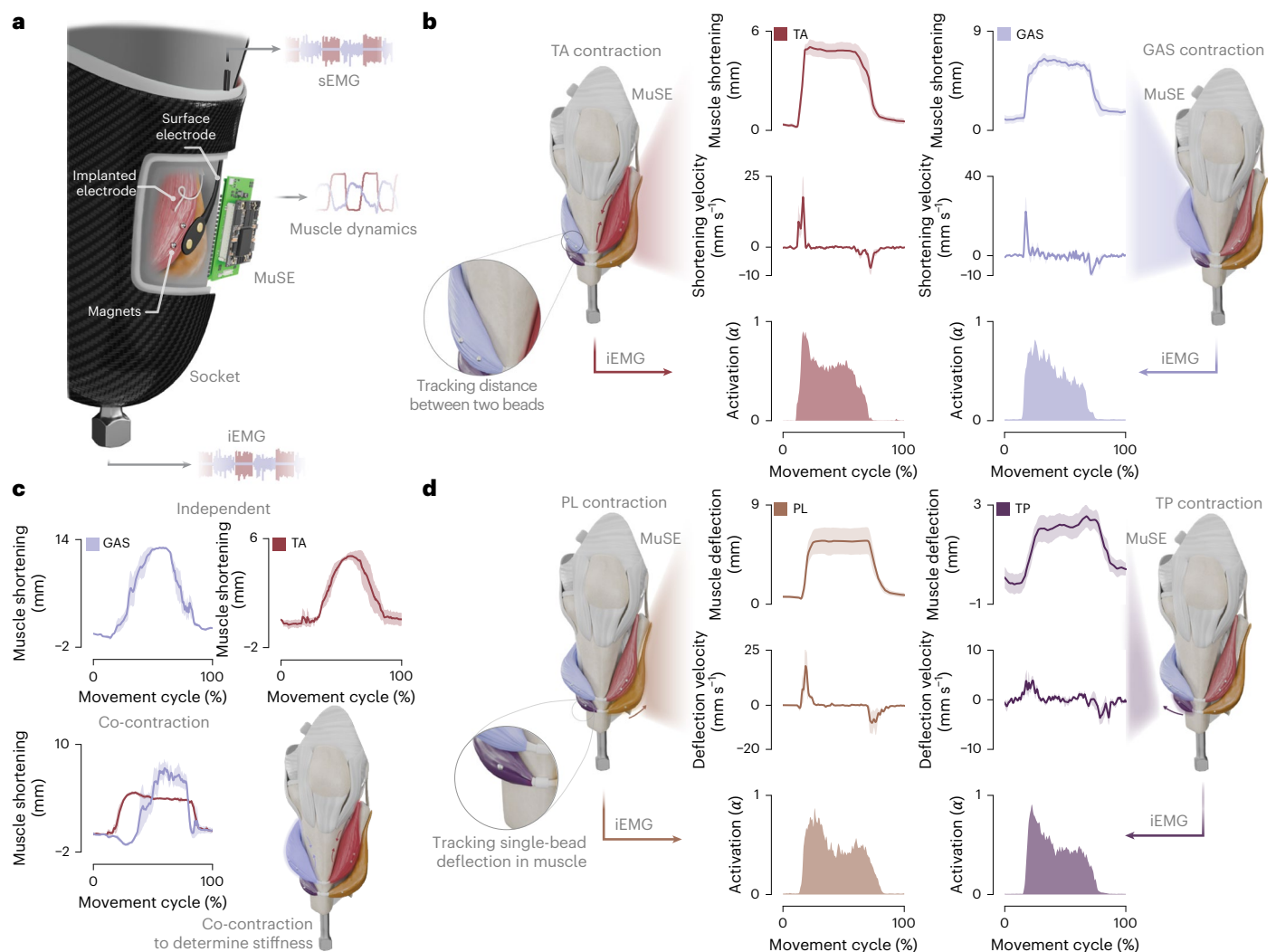


Fig. 3 | Continuous wireless sensing of muscle dynamics in vivo. a, Experimental implementation of all three interfaces (MuSE, iEMG and sEMG) with residual muscles. Specifically, we implanted magnetic beads and intramuscular electrodes into each muscle and positioned surface electrodes on the skin adjacent to each muscle. Participants wore a prosthetic socket to allow mounting of the sensor boards. iEMG was accessed through the signal port of a percutaneous implanted device. MuSE systems tracked bead positions through the socket, liner and skin. **b**, Evaluation of signal characteristics within the ankle muscles, specifically the tibialis anterior and GAS muscles, with two magnetic beads each. The plots represent the average muscle shortening and velocity from MuSE and muscle activation from iEMG at 100% perceived effort for a 5-s isometric contraction movement cycle ($n = 3$ trials per participant; $n = 2$

participants). **c**, Muscle deflections from participant 3, who was asked to slowly ramp up muscle contractions and then ramp them down again, first for each muscle independently and then for both simultaneously, over a 5-s movement cycle ($n = 3$ trials per participant per movement type; $n = 1$ participant).

d, Assessment of signal characteristics within the subtalar muscles, specifically the peroneus longus (PL) and tibialis posterior (TP) muscles, with one magnetic bead each. For participant 2, tibialis posterior characteristics were calculated from the peroneus longus stretch. The plots represent the average muscle deflection and velocity from MuSE and muscle activation from iEMG at 100% perceived effort for a 5-s isometric contraction movement cycle ($n = 3$ trials per participant; $n = 2$ participants). All shaded regions for muscle deflection and velocity indicate s.e.m.

Each participant received an osseointegrated implant system integrating both implanted electrodes and magnetic beads (Fig. 3a). The beads were implanted into residual muscles—two magnets per ankle muscle and one per subtalar muscle (Methods). The bionic reconstruction also included agonist–antagonist myoneural interface (AMI) surgery (Methods). This approach enables proprioceptive feedback and demonstrates enhanced prosthetic control compared with conventional amputations^{21,45}. Two AMI muscle pairs were created for each participant: the lateral gastrocnemius (GAS) and tibialis anterior for ankle control; and the tibialis posterior and peroneus longus for subtalar control (Fig. 3b,d).

We simultaneously acquired signals from three sensing platforms: MuSE, iEMG and sEMG. Participants wore a custom prosthetic socket with up to four MuSE systems positioned over each muscle,

with surface electrodes placed at the same anatomical landmarks. The MuSE systems achieved simultaneous tracking of multiple implanted magnets through the prosthetic socket across tissue depths of 3–6 cm (Supplementary Fig. 17). In participant 2, overlying GAS magnets, deep implantation and limited placement space for the MuSE systems prevented reliable tibialis posterior tracking, so we inferred tibialis posterior activation from peroneus longus magnet deflection throughout the study. This single-magnet stretch signal was sufficient to resolve inversion from eversion intent. During maximal voluntary contractions, MuSE revealed mean muscle fascicle shortening at the centre of the movement of 6.2 mm for the GAS and 4.8 mm for the tibialis anterior, and mean muscle movement of 5.7 mm for the peroneus longus and 2.2 mm for the tibialis posterior, with muscle length profiles showing rapid contraction and sustained isometric

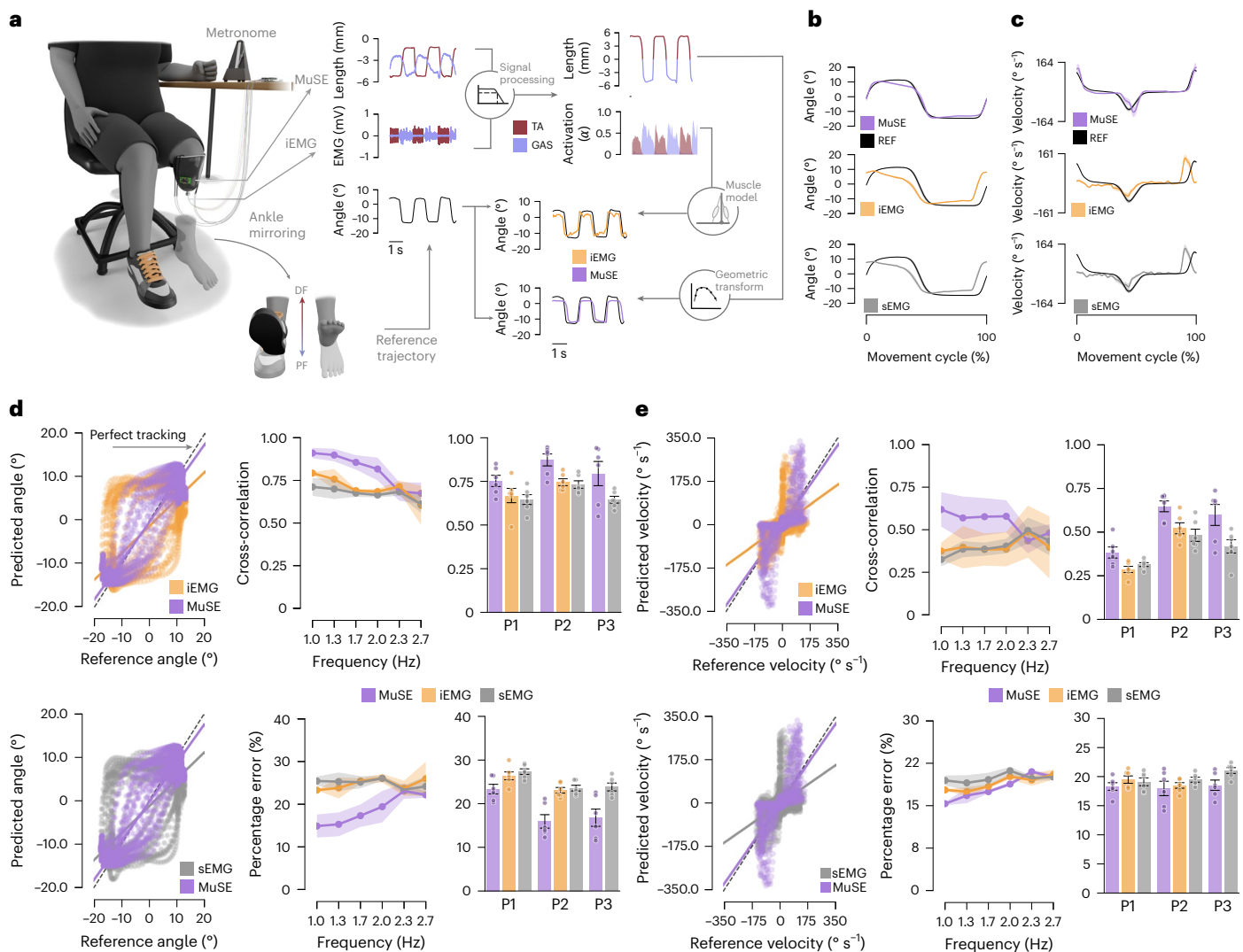


Fig. 4 | MuSE enables accurate prediction of joint kinematics. **a**, Evaluation of mirrored joint kinematics between an intact ankle and a phantom ankle as a participant tracks the full range of movement at a specified frequency designated through a metronome. Representative plots depict the reference trajectory generated from intact ankle kinematics, whereas EMG and MuSE signals are collected from the amputated side tibialis anterior and GAS residual muscles. These signals are processed into activation and combined length signals. Combined length signals undergo geometric transformation, whereas activation signals pass through a bilinear muscle model to generate modelled ankle kinematics for comparison with the reference trajectory. **b**, Representative plots for participant 2, showing ankle angle trajectory comparisons across all interfaces between reference and modelled kinematics at a movement frequency of 1 Hz ($n = 14$ cycles within the movement window). **c**, Representative plots for participant 2, showing ankle velocity trajectory comparisons across all interfaces between reference and modelled kinematics at a movement frequency of 1 Hz

($n = 14$ cycles within the movement window). **d, e**, Left: example scatter profiles of reference angle plotted against predicted angle (**d**) and reference velocity plotted against predicted velocity (**e**) for iEMG versus MuSE (top) and sEMG versus MuSE (bottom) during the trial of participant 2 at 1 Hz. The dashed lines represent perfect tracking between the two. Solid lines represent the lines of best fit for MuSE, iEMG and sEMG. Middle: cross-correlation (top) and percentage error (bottom) for ankle angle (**d**) and velocity (**e**) tracking at each frequency, averaged across the three participants ($n = 6$ frequencies per participant; $n = 3$ participants). Right: bar graphs showing the results for cross-correlation and percentage error broken down by participant (P1–3). Statistical significance in **d** and **e** was determined by two-sided Wilcoxon signed-rank test with Bonferroni correction. All bars indicate means and s.e.m. All shaded regions indicate s.e.m. DF, dorsiflexion; PF, plantarflexion. 3D models reproduced with permission from TurboSquid.

phases (Fig. 3b,d). MuSE enabled direct calculation of muscle fascicle shortening velocities from length measurements. The system also allowed one participant to demonstrate muscle contraction ramping and coordinated co-contraction patterns within muscle pairs, indicating the potential for impedance modulation control for dynamic neuroprosthetic performance (Fig. 3c). We observed differences in the signal characteristics between MuSE and EMG during sustained isometric contractions. EMG signals exhibited temporal decay throughout the contraction period, whereas MuSE signals remained stable (Fig. 3b), providing consistent muscle-state information throughout sustained contractions. This decay in EMG amplitude does not fully

reflect mechanical changes in the underlying isometric muscle state, suggesting that MuSE may possess advantages for real-time neuroprosthetic interface applications. In addition, no complications occurred from magnetic bead implantation across the three participants over an average implantation period of more than one year (Methods and Supplementary Table 2).

MuSE as a human–machine interface

To evaluate the MuSE system's ability to work as a neuroprosthetic interface compared with standard EMG methodology, we designed two experiments. A free-space mirroring task assessed how closely

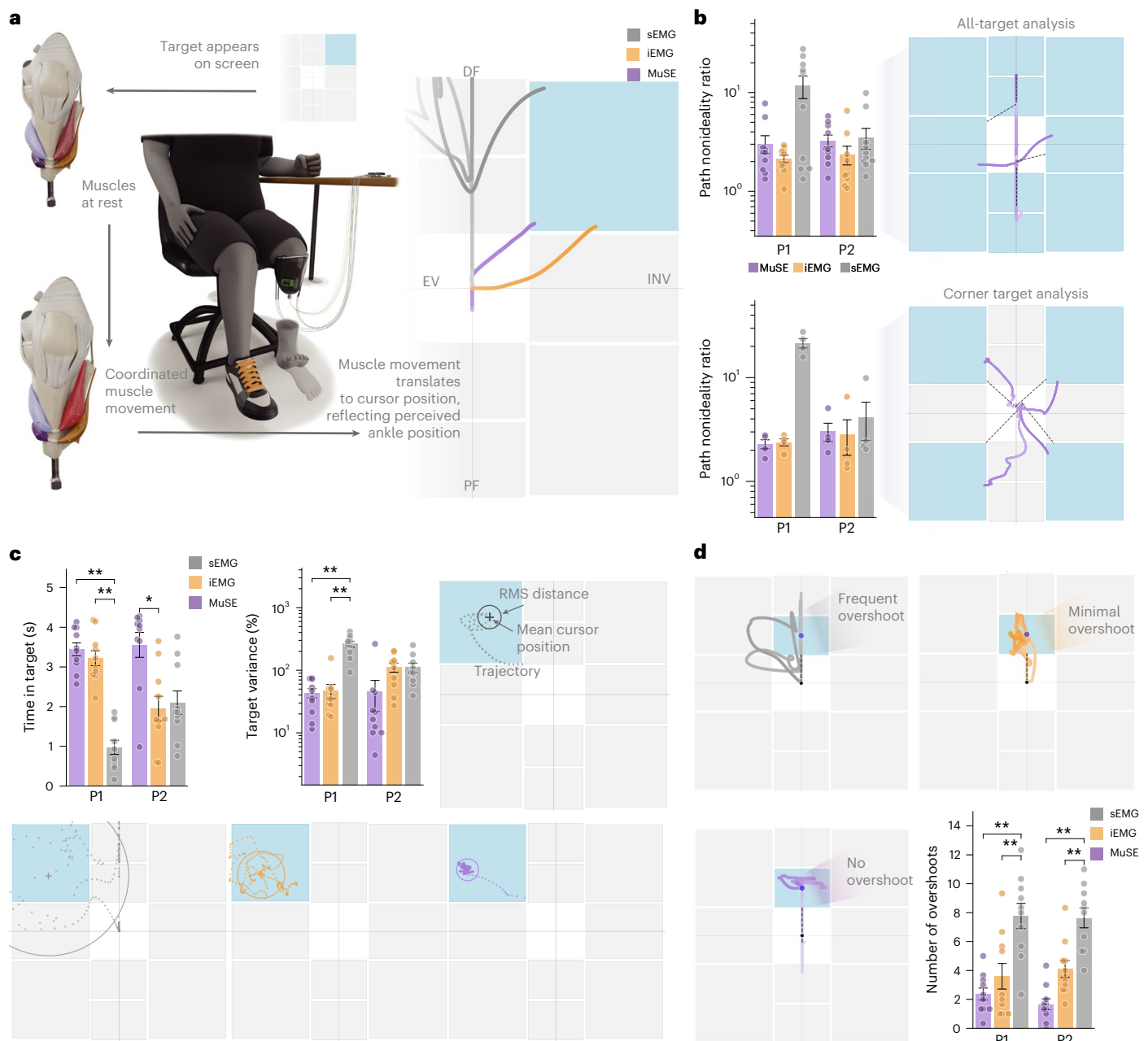


Fig. 5 | MuSE exhibits stable neuroprosthetic performance. a, Virtual 2D map representing the ankle range of motion, with the horizontal axis representing subtalar motion (left, eversion (EV); right, inversion (INV)) and the vertical axis representing ankle motion (up, dorsiflexion; down, plantarflexion). Representative cursor trajectories from the MuSE, iEMG and sEMG interfaces to a corner target are shown for participant 1, requiring simultaneous muscle activation. **b**, Path nonideality of cursor trajectory to target for all targets together ($n = 2$ participants; $n = 3$ trials per participant; $n = 10$ paired targets averaged across trials) and corner targets only ($n = 2$ participants; $n = 3$ trials per participant; $n = 4$ paired targets averaged across trials). **c**, Summary of target reach performance metrics, including time in target and cursor variance ($n = 2$ participants; $n = 3$ trials per participant; $n = 10$ paired targets averaged across

trials). For participant 1, $**P = 0.00586$ for each significant comparison. For participant 2, $*P = 0.0176$ for the time-in-target comparison of MuSE with iEMG. Representative plots from participant 1 demonstrate cursor variance across all interfaces. The dotted lines represent the trajectory after target reach. Plus signs indicate mean cursor position and circles indicate root mean square (RMS) deviation from the mean cursor position after target reach. **d**, Summary of target overshoot performance ($n = 2$ participants; $n = 3$ trials per participant; $n = 10$ paired targets averaged across trials). For participants 1 and 2, $**P = 0.00586$ for each significant comparison. Statistical significance was determined by two-sided Wilcoxon signed-rank test with Bonferroni correction. All bars indicate means and s.e.m. 3D models reproduced with permission from TurboSquid.

each interface reconstructed single-DOF joint kinematics after offline optimization, comparing electrical and mechanical sensing as estimators of volitional joint movement (Fig. 4a, Supplementary Video 3 and Supplementary Note 4). A virtual two-dimensional (2D) cursor task then evaluated real-time multi-DOF control across each interface, informing the relative contributions of invasive selectivity and

signal modality as control inputs (Fig. 5a, Supplementary Video 4 and Supplementary Note 5).

Representative tracking performance at 1 Hz demonstrated that MuSE signals closely matched reference trajectories, whereas EMG-based reconstruction exhibited larger deviations and noticeable temporal shift (Fig. 4b,c). Across all three participants, MuSE consistently

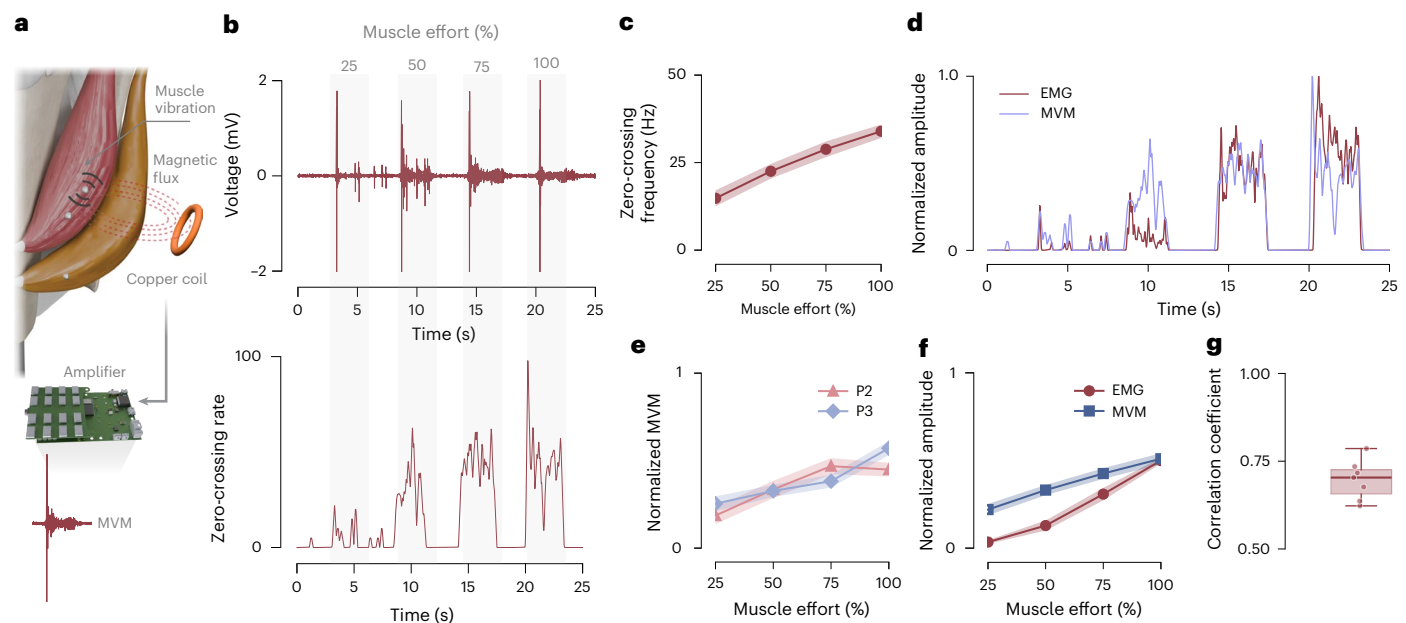


Fig. 6 | Magnetic detection of muscle activation. **a**, Schematic of the MVM system, showing inductive coil placement near an implanted permanent magnet to detect magnetic flux changes during muscle contractions. **b**, Top: representative MVM signals from participant 2 showing processed voltage measurements corresponding to different perceived muscle effort levels (25, 50, 75 and 100% maximum voluntary contraction, as indicated by the shaded regions). Bottom: corresponding zero-crossing rate over time after processing the voltage measurements. **c**, Relationship between muscle effort level and mean zero-crossing frequency across the effort time window for participants 2 and 3 ($n = 7$ trials per participant; $n = 2$ participants). **d**, Representative results from participant 2 of a time-series comparison of simultaneously recorded

and normalized EMG and MVM measurements. **e**, Mean normalized MVM signals comparing the responses of participants 2 and 3 across varying muscle effort levels ($n = 7$ trials per participant; $n = 2$ participants). **f**, Comparison of the mean normalized EMG amplitude responses from participant 2 and the mean normalized MVM measurements from both participants for different muscle effort levels ($n = 7$ trials per participant; $n = 1$ participant for EMG; $n = 2$ participants for MVM). **g**, Correlation statistics for participant 2 between EMG and MVM measurements across all trials ($n = 7$ trials). The central line represents the median, the whiskers correspond to the minimum and maximum values and the box bounds represent the 25th and 75th percentiles. In the line plots, the shading represents s.e.m.

achieved higher mean cross-correlation and lower mean percentage error for angle tracking compared with both sEMG and iEMG, although within-participant differences did not reach significance (Fig. 4d). This trend was most apparent in participant 2, whose mean cross-correlation was 0.873 ± 0.034 for MuSE compared with 0.745 ± 0.020 for iEMG and 0.732 ± 0.021 for sEMG, with mean percentage errors of 15.94 ± 1.53 , 23.07 ± 0.64 and $23.57 \pm 0.64\%$, respectively. Velocity tracking showed a similar but weaker pattern, with MuSE achieving higher mean cross-correlations and lower mean percentage errors than both EMG modalities in each participant (Fig. 4e). The mean velocity cross-correlation was lower overall than for angle tracking, reflecting the increased noise and phase sensitivity inherent to higher-frequency tracking. The similar mean tracking performance between sEMG and iEMG may be attributable to the high isolated muscle selectivity and SNR afforded by both modalities when sensing the GAS and tibialis anterior, which are large and superficial muscles. Scatter plots of predicted versus reference trajectories illustrated signal differences, with the MuSE data clustering tightly around perfect tracking, in contrast with EMG-based predictions, which showed greater deviations (Fig. 4d,e). Signals from MuSE demonstrated a waveform that closely approximated the target joint kinematics. EMG signals, when integrated with an optimized neuromuscular model, tracked intended joint kinematics with higher mean percentage error than MuSE when averaged across the tested frequency range. Signals conveying muscle dynamics required geometric scaling from muscle displacement to ankle rotation, directly relating muscle mechanical state to joint position. In contrast, the EMG model replicated the target motion less closely, possibly because the relationship between activation and force is dependent on muscle length and velocity⁴⁶. Whereas EMG necessitates complex filtering to extract meaningful control signals, the direct muscle length information

provided by MuSE may reduce cumulative processing errors, delay and loss of information.

For cursor path trajectories in the two-DOF task, iEMG qualitatively demonstrated lower mean path nonideality in both participants (Fig. 5b), with similar patterns for corner targets. Once the target was reached, the mean cursor variance was lowest and the mean time in target longest for MuSE in both participants. Both implanted interfaces significantly outperformed sEMG on these metrics in participant 1, and MuSE significantly outperformed iEMG on time in target in participant 2 (Fig. 5c). In participant 2, neither implanted interface significantly outperformed sEMG on these stability metrics. However, MuSE maintained a larger mean performance margin over sEMG than iEMG did. Contributing factors in participant 2, such as cross-talk in the implanted peroneus longus channel with GAS activation, may have compromised the selectivity advantage typically afforded by implanted electrodes, affecting the iEMG outcomes (Supplementary Fig. 18). MuSE and iEMG also demonstrated significantly fewer overshoot events compared with sEMG in both participants (Fig. 5d). These results may reflect differences in signal characteristics. The MuSE system provides continuous mechanical measurements of muscle contraction, allowing sustained positioning during isometric contractions, whereas EMG signals can exhibit temporal decay over a sustained hold. The significantly fewer overshoots observed for both implanted interfaces relative to sEMG suggest a selectivity advantage from targeted sensing for multi-DOF control (Supplementary Fig. 19).

Muscle activation sensing

We used a passive coil in conjunction with the implanted magnets to measure muscle activation through bead vibration (Fig. 6a). This passive coil can be added to the MuSE system as an additional module

(Supplementary Note 6). The level of neural activation of a muscle is determined by the firing rate and recruitment of motor units controlling its fibres⁴⁷. We reasoned that vibrations generated by muscle fibres, which are representative of neural signals, can be detected from changes in the magnetic flux resulting from the corresponding vibrations of implanted magnets. This new technique, which we call magnetovibrometry (MVM), represents a method related to mechanomyography⁴⁸ that avoids the impedance artefacts that are inherent in mechanical contact methods. Previous studies have demonstrated that muscle vibration (mechanomyography) can be measured mechanically⁴⁹ or acoustically⁵⁰. MVM may provide an alternative approach with similar responses across two participants.

Voltage recordings typically showed decreasing amplitude and increasing frequency with greater muscle effort (Fig. 6b). The mean zero-crossing frequency increased with muscle effort, possibly consistent with higher muscle twitch frequencies resulting from increased neural firing rates (Fig. 6c). To compare MVM with EMG, simultaneous measurements were collected from implanted electrodes in participant 2. Normalized MVM signals broadly matched those of EMG in both amplitude and temporal profile for this participant (Fig. 6d). Both participants primarily showed increasing normalized MVM signals with increasing effort (Fig. 6e). The normalized MVM response increased with muscle effort in a pattern comparable to that of EMG (Fig. 6f), with a mean correlation coefficient of 0.6966 between the two modalities in participant 2 (Fig. 6g). In agreement with previous findings, EMG is approximately linear for most of the range of percentage efforts, but becomes nonlinear at low levels of muscle activity⁵¹. Previous mechanomyographic work describes either amplitude or frequency increases with muscle effort, depending on the sensing modality^{50,52}. With implanted magnets positioned near muscle fibres, MVM generally exhibited increasing signal frequency and decreasing amplitude, consistent with force dynamics at higher motor unit firing rates. The observed frequencies were qualitatively aligned with previously reported mechanomyography findings⁵³.

Discussion

The MuSE system demonstrates that real-time, wireless human muscle dynamics can be measured by combining permanently implanted 3-mm-diameter magnetic beads with custom electronics, a high-density sensor array and an information-theoretic tracking algorithm. MuSE can provide neuroprosthetic control information directly from muscle mechanics, potentially offering a more scalable and intuitive pathway towards complex human–machine control⁵⁴. This system has broader potential in human–machine interface domains such as wearable robotic control and rehabilitation monitoring, as well as biomechanical studies in both humans and animals⁵⁵. A key advantage is that passive implants may remain unaltered while new sensors, algorithms and system integration can progressively unlock novel sensing capabilities over time. For instance, by combining magnetomicrometry with MVM using the same implants, MuSE could simultaneously capture muscle length, velocity and activation information, potentially providing real-time muscle-state and force estimation through a Hill-type muscle model. The MuSE system's localization and design principles can extend beyond muscle sensing to applications such as tracking electronics within the gastrointestinal tract⁵⁶ or localizing surgical devices⁵⁷. The simulation framework can be adjusted with sensor geometry, sensitivity, magnet dimensions and expected implantation depths to assess feasibility for new applications.

Several implementation considerations remain for future development of the MuSE system. First, it is critical when implanting a magnet pair to implant the magnets along a muscle fascicle. If the magnet pair is implanted with a separation vector aligned differently than the muscle pennation, the signal may be distorted in a way that cannot be directly mapped back to fascicle contraction⁵⁸. Second, a muscle instrumented with a single magnet introduces measurement uncertainty because

the system cannot distinguish actual magnet motion due to muscle contraction versus a motion artefact caused by sensor board displacement. Despite enabling subtalar control, single-magnet tracking may have limited performance. This can be mitigated by prioritizing two magnets within each contractile muscle belly, such that their relative separation distance in real time accounts for sensor board movement artefacts⁵⁹. Third, the tracking feasibility depends on the spatial arrangement of magnets relative to one another and the sensor board. Surgical planning should minimize the magnet depth relative to the sensor array while also ensuring an adequate separation distance to mitigate the migration risk. Considerations of this nature are particularly important for upper-extremity applications where overlapping forearm extensors and flexors tighten the spacing constraints. Fourth, in the case of polyarticular muscles, precise mechanical sensing inherently measures the total muscle contractile state caused by movement of both the phantom joint and other biological joints for which the muscle spans. Although participants maintained constant knee angles to isolate ankle dynamics in this study, future implementations must decouple confounding effects of biarticular GAS movements caused by changes in knee position, such as through the fusion of knee position and muscle-state information⁶⁰. This behaviour may be more pronounced during dynamic activities such as walking, where cyclical knee flexion and extension alter the resting length of the GAS.

Although our results were generally consistent across the three participants, future work must evaluate tracking and implant stability over extended periods and in expanded cohorts to establish the longitudinal robustness and safety required for clinical translation. Accordingly, these findings support feasibility but not a generalizable clinical benefit. The preliminary neuroprosthetic tasks here were limited to free-space position control in a static environment; real-time control during gait remains to be demonstrated. Finally, the large contractile amplitudes observed may be partially attributed to the AMI surgical construct, which provides enhanced mechanical strain that amplifies detectable fascicle length changes. Future work should investigate integrating the MuSE system with other surgical constructs, such as regenerative peripheral nerve interfaces, to assess its performance across different anatomical configurations.

Methods

MuSE sensor electronics

The MuSE electronics architecture comprises three components: (1) a custom sensor board; (2) a custom carrier board; and (3) an FPGA system-on-module (SoM). The sensor board contains 640 tunnel magnetoresistive magnetometers (LIS3MDL; STMicroelectronics) employing a serial peripheral interface (SPI) communication protocol. The array is organized as 32 independent SPI column interfaces, with each column serving 20 rows of sensors that share the serial data line. The sensors are spaced 2.7 mm apart in the 16-column (double-sided) direction and 3.6 mm apart in the 20-row direction. Four distributed SPI clocks (10 MHz) are distributed across the 32 columns (eight columns per clock) to achieve clock signal integrity. The rows are organized by a cascaded shift register chain (74LVC594ABQ,115; Nexperia) that drives 20 chip-select lines. A sensor is uniquely addressed at the intersection of one SPI column (data bus) and one active chip-select row.

Each of the four clock lines drives 160 LIS3MDL magnetometers (eight columns by 20 rows), presenting a high cumulative capacitive load. We implemented high-current complementary push–pull drivers using discrete metal-oxide-semiconductor field-effect transistors (SSM6LS6FE,LM; Toshiba) capable of sourcing and sinking high instantaneous current to actively drive both rising and falling clock edges. The signal path for each clock line begins with a voltage-level step-up from 1.8 V FPGA logic to 3.3 V sensor logic levels via dual-channel voltage translators (SN74AVC2T244DQMR; Texas Instruments), which directly drive the gates of complementary metal-oxide-semiconductor field-effect transistor pairs.

MuSE computing electronics and packaging

The carrier board hosts the FPGA SoM (Mercury XU5; Enclustra), power management, timing and input/output needed to operate the 640-sensor array. A 12-V input drives the board power and a voltage buck converter (TPSS64208DDCT; Texas Instruments) outputs 3.3 V for sensor power supply. High-speed digital interfaces are routed from the FPGA to the sensor board as the carrier board exposes the 32 parallel SPI column channels and 1.8-V logic lines. Ethernet is provided for wired communication, and a WiFi module (LBEE5KL1DX; Murata) provides wireless communication at 2.4 GHz through a flexible antenna (FXP830; Taoglas). A 100-MHz oscillator (ASEMB-100.000MHZ-LY-T; Abracon) supplies a stable timing reference for the SoM. A custom-designed aluminium heatsink and 12-V fan (RS5010B12L-FA; Runda) were added to thermally regulate the FPGA chip. A 1-mm layer of copper pads was placed on top of the sensors to allow them to conduct heat away and reduce thermal drift. The sensor board and carrier were connected through either a flex-PCB connector or a rigid connector and the FPGA was mounted to the carrier through rigid connectors. An enclosure was fabricated using 3D printing to protect the electronics, with final dimensions of 70 mm × 100 mm × 48 mm.

Information-based tracking algorithm

Based on the dipole tracking principles of Taylor et al.³⁹, magnet position and orientation were estimated from the array of 3D magnetic field measurements. In addition to the magnet state, the uniform disturbance field state was estimated. This was done with an extended information filter (INFO) framework. The information filter represents the system state through an information matrix Y_0 (inverse covariance P_0^{-1}) and information vector y_0 (inverse covariance multiplied by the state vector $P_0^{-1}x_0$), enabling efficient processing of systems with significantly more measurements than states. The INFO operates with an information matrix Y and information vector y , initialized as:

$$Y_0 = P_0^{-1}$$

$$y_0 = Y_0 x_0$$

where P_0 is the initial covariance matrix and x_0 is the initial state estimate.

The algorithm computes information from each sensor measurement as $H^T R^{-1} H$, where H is the measurement Jacobian and R is the measurement noise covariance. For each measurement update, at time sample k , the information matrix and vector are updated as:

$$S_k = H_k^T R^{-1} H_k$$

$$Y_{k|k} = Y_{k|k-1} + S_k$$

$$y_{k|k} = y_{k|k-1} + H_k^T R^{-1} \tilde{z}_k$$

where S_k represents the information contributed by the new measurement, $\tilde{z}_k$ is the augmented innovation and $k|k$ denotes the information at time k given the measurement up to and including at time k . The optimal state estimate $x_{k|k}$ is derived as:

$$x_{k|k} = Y_{k|k}^{-1} y_{k|k}$$

Magnet tracking simulation and benchtop validation

The simulation framework reproduced sensor measurements by generating expected fields from inputting true parameters of the magnet state and adding Gaussian white noise representative of the sensor noise. All simulation trials used modelled sensors with added Gaussian noise (2.5 μ T standard deviation) and tracked magnetic beads with a dipole strength of 1.39 nT·m³, matching the estimated implanted bead strength. Static and dynamic trials included a uniform geomagnetic disturbance field with a magnitude resembling physical values (−20 μ T x direction; 20 μ T y direction; −80 μ T z direction). The sensors were

simulated at a 1-kHz sampling rate with their geometry matching that of the physical sensor board. Comparative analyses between Levenberg–Marquardt and extended information filter (INFO) algorithms used identical analytical dipole field models and Jacobian equations.

For single-magnet static trials, tracking performance was evaluated across 52 spatial configurations, testing four depths (30, 40, 50 and 60 mm) from the sensor array with 13 x – y positions per depth generated from an arrangement of x coordinates (0, 10, 20, 30 and 40 mm) and y coordinates (0, 8, 16, 24 and 32 mm). For sensor density analysis, five configurations were tested with systematically reduced active sensor counts while maintaining spatial distribution: 60, 120, 240, 320 and 640 active sensors, with a single simulated magnet positioned at (0, 0, 60) mm. Each unique position underwent two independent trials, whereas density analysis used ten independent trials per sensor configuration. All trials contained identical random initial parameter estimates for both algorithms to enable direct comparison, with initial conditions randomly generated within the sensor coverage volume. If either algorithm diverged due to the non-convexity of dipole modeling, another initial guess was initialized for that trial. Each algorithm performed 4,000 estimation iterations, with final performance metrics calculated from the last 500 iterations to ensure steady-state convergence. For simulated dynamic trials, we assessed magnet motion using pre-computed trajectories, where both algorithms first reached steady-state convergence of the initial state before tracking. Because each Levenberg–Marquardt step was initialized from the preceding estimate, some solves terminated when the update became negligibly small.

Performance across each trial was quantified using mean absolute error (MAE):

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N \|\hat{\mathbf{p}}_i - \mathbf{p}_{\text{true}}\|$$

and positional error variance:

$$\sigma^2 = \frac{1}{N-1} \sum_{i=1}^N (\|\hat{\mathbf{p}}_i - \mathbf{p}_{\text{true}}\| - \text{MAE})^2$$

where $\hat{\mathbf{p}}_i$ represents the estimated position or distance, $\mathbf{p}_{\text{true}}$ is the true position or distance and $N = 500$ steady-state iterations.

For benchtop testing with the physical-magnet-tracking embedded system, two magnets were positioned at $[\pm 20, 0, z]$ mm, spaced 40 mm apart, across four depths (30–60 mm). Both tracking algorithms were implemented in a real-time C++ framework and compared algorithm latencies and estimation errors by analysing the final 500 iterations at steady-state convergence. For additional drift and noise characterization, two magnets were positioned at $[\pm 20, 0, 40]$ mm. To investigate the effect of temperature and electromechanical noise on sensor performance, tracking was performed without cooling and compared with the final version of the device. Drift was captured across 1 h of continuous tracking.

Clinical study design and surgical implementation

This study was conducted under a registered clinical trial (NCT06391697), which aimed to investigate the clinical safety and efficacy of the magnetic bead tracking system in conjunction with the implanted electrode system (enhanced osseointegrated prostheses for the rehabilitation of amputees (e-OPRA); Integrum). The study protocol and implants underwent US Food and Drug Administration Investigational Device Exemption approval, as well as institutional review board (IRB) approval at both the Massachusetts Institute of Technology (MIT) and Mass General Brigham (MGB), where experiments were completed under supervision. Both systems were implanted at the transtibial amputation level in combination with AMI bionic reconstruction.

We recruited three participants, two of whom underwent an acute transtibial amputation that received both magnetic bead and

implanted electrode implantation, and one of whom had a pre-existing amputation with revision to add the magnetic bead tracking system and reimplantation of the e-OPRA system. This participant was previously part of a related study (NCT05249049), which investigated the implanted electrode system with a robotic prosthesis. All surgeries and pre-screening to determine eligibility were conducted at Brigham and Women's Hospital under MGB IRB protocol 2024P000006. Consent for both surgery and human participant testing fell under the MGB protocol, which the MIT IRB ceded to. Before surgery and testing, participants provided written consent at both MIT and MGB sites. A full detailed list of both inclusion and exclusion criteria and interventions can be found at ClinicalTrials.gov under accession code NCT06391697. The cohort of three participants underwent repeated measures of tasks, and the period of recruitment and data collection for this accompanying part of the study occurred from 2023 to 2025. Participants were compensated US\$20 h⁻¹ according to MIT policy. The study protocol can be made available by the corresponding authors upon reasonable request.

The surgical implantation of the magnetic beads and e-OPRA systems was split across two separate stage procedures that were spaced 3–6 months apart. The first stage encompassed: (1) soft-tissue muscle constructs; (2) osteotomy; and (3) implantation of a titanium BioHelix fixture (Integrum), intramuscular electrodes and magnetic beads. Initially, muscles were dissected to create two AMI pairs: the GAS and tibialis anterior for prosthetic ankle joint control; and the tibialis posterior and peroneus longus for subtalar joint control. After AMI creation and osteotomy, subsequent interface implantation included both permanent implanted electrodes and magnetic beads. Two magnets were implanted into each ankle AMI muscle belly along its longitudinal axis, taking care to place the magnets along a muscle fascicle. Each muscle's bead pair was used to wirelessly track that muscle's length and speed, whereas eight bipolar implanted electrode pairs captured the isolated muscle activation of each AMI muscle construct. For all implanted magnets, the conservative target separation distance for any magnet-to-magnet pair was 4 cm for all muscle contractile states, to prevent bead migration within the first six weeks³⁵. Due to this limitation, only one magnet could be implanted into each of the subtalar muscles to prevent exceeding the required separation distance within the residual limb. Magnets were implanted using one of two approaches: either through a small incision to create a muscle pocket for bead placement; or by direct insertion into the muscle tissue. Implantation was performed using either a bead inserter (Halifax Biomedical) or nonmagnetic surgical tweezers. Both participants 1 and 2 received a total of six magnets; two for each ankle AMI muscle and one for each subtalar AMI muscle. As participant 3 underwent an amputation revision procedure, only two magnets were placed in each ankle AMI muscle for a total of four magnets, as subsequent scar tissue prevented surgical access to the deeper subtalar muscles.

Following an initial recovery from the first stage, participants 1 and 2 received the second stage, which involved placing the eAbutment (Integrum) into the BioHelix fixture, allowing both: (1) accessibility to the implanted electrode connections through a 16-pin connector; and (2) mechanical connection of an external prosthesis to the osseointegrated implant. No complications, adverse events or participant discomfort were related to the magnetic beads. No measurable bead migration occurred in any of the three participants within the reported study window. Participant 2 had to receive a tightening of their fixture and abutment during the study, whereas participant 1 reported no complications with the e-OPRA system. As participant 3 had to receive a fixture and abutment replacement due to loosening of the osseointegrated implant, their implanted electrodes were not accessible in this corresponding part of the study.

EMG and MuSE implementation

To simultaneously capture data from all three neural interfaces (MuSE, sEMG and iEMG), all measurement hardware was connected

concurrently. We utilized the EMG acquisition system developed by Yeon et al.⁶¹, connecting both implanted electrodes from the osseointegrated connector and surface electrodes to the system for each muscle, allowing up to six bipolar channels to be measured concurrently. All signals were sampled at 1 kHz, with EMG signals processed through bandpass filtering (fourth-order Bessel filter; 20–330 Hz passband) and then rectification and low-pass filtering for EMG envelope generation (fourth-order Bessel filter; 10 Hz cutoff). EMG envelope signals were normalized between the noise floor and maximum voluntary contraction, with subsequent bilinear activation dynamics applied to compute muscle activation signals²¹. The MuSE raw muscle length signals were low-pass filtered (fourth-order Bessel filter; 10 Hz cutoff) to capture the physiological bandwidth of muscle movement.

For MuSE system positioning, participants wore a custom socket with an opening to accommodate the osseointegrated implant, enabling static mounting of tracking hardware over target muscles. Surface electrodes utilized the same flexible, thin-film design developed by Yeon et al.⁶¹ to capture sEMG signals within the socket. Surface electrode placement was guided by palpation of known AMI construct locations, with electrodes positioned directly over these anatomical landmarks. To determine optimal MuSE board placement across the socket surface, we scanned each palpated AMI construct region using the array of magnetic field sensors. For each muscle, we identified locations containing maximum magnetic field strength, whether from magnet pairs or single magnets, and marked these positions before adhering the boards to the socket. In most configurations, we allocated one dedicated board per muscle, positioning up to four boards around the socket perimeter for up to four muscles. Board outputs comprised either distance measurements between magnet pairs or, for muscles with single magnets, deflection measurements as the muscle underwent volitional activation.

Free-space mirroring task

A free-space mirroring task adapted from Shu et al.⁶² was used to evaluate how each interface can predict intended joint kinematics. To generate a reference trajectory, participants were instructed to mirror intact ankle kinematics with their perceived phantom ankle motion while we measured MuSE, sEMG and iEMG signals simultaneously from the residual limb. Participants sat on a stool to ensure full range of motion, and a metronome track with the tempo ranging from 60 to 160 beats per minute (1.0–2.7 Hz) in increments of 20 beats per minute indicated, on each beat, to move to one end of the range of motion (for example, from dorsiflexion to plantarflexion). The intact ankle was instrumented with a goniometer (Biometrics) to capture ankle kinematics. All signals were digitally synced and zeroed at the ankle rest position. Angular data were collected at 1 kHz and low-pass filtered (fourth-order Bessel filter; 10 Hz cutoff). Each trial lasted 30 s. To model the intended ankle kinematics of the phantom limb from muscle activation collected by iEMG and sEMG, a bilinear muscle model of a single-DOF joint actuated by a muscle pair was applied (Supplementary Note 4). The model's parameters were optimized to minimize the mean squared error between the experimentally observed reference and modelled kinematics.

To create a direct kinematic estimate from the MuSE, the two length signals from the tibialis anterior and GAS muscles were combined by fusing the opposing length changes into a single, bidirectional signal representing the intended joint angle. To determine the geometric transformation between muscle length changes and joint space, a second-order polynomial was optimized to minimize the mean squared error between the MuSE signal and the intact joint angle. To quantify performance across all metronome tempos and participants, we evaluated both the predicted joint angle and joint angular velocity, including both the percentage error between reference and predicted values and the cross-correlation coefficient at zero lag.

2D virtual neuroprosthetic interface task

Outcome measures for evaluating neuroprosthetic control performance were derived from free-space control experiments conducted with visual feedback adapted from Clites et al.⁴⁵. Participants controlled a virtual prosthetic joint position represented as a cursor across a 2D graphical user interface (GUI) using either an sEMG, iEMG or MuSE controller (Supplementary Note 5). Plantarflexion–dorsiflexion was represented on the vertical y axis and inversion–eversion on the horizontal x axis.

Before experimental data collection, muscle scaling parameters were fine-tuned during a calibration phase where participants practised reaching targets on the GUI and confirmed that they could adequately reach each target while providing feedback on movement sensitivity. Participants performed three sequential volitional control tasks within 5 s: (1) move the cursor to a rectangular target window in joint angle space; (2) maintain the cursor within this target; and (3) return the cursor to neutral. Following familiarization with the experiment, participants performed the task at ten targets presented in randomized order. The sEMG and MuSE interfaces were tested within the same session in randomized order to minimize fatigue effects. As the 2D cursor task required four channels for each EMG interface and the acquisition hardware supported a maximum of six simultaneous channels, sEMG and iEMG could not be recorded concurrently and the iEMG interface was therefore evaluated in a separate session. The iEMG GUI session followed an identical methodology to the other interfaces, including calibration, target randomization and rest periods. Each participant took part in three trials for each interface.

Performance was quantified using path nonideality, time in target, number of overshoots and target variance. Path nonideality was defined as:

$$\text{Path nonideality} = \frac{L_{\text{path}}}{\|\mathbf{p}_{\text{ideal}} - \mathbf{p}(0)\|}$$

where L_{path} is the length of the cursor trajectory to the target entry and $\mathbf{p}_{\text{ideal}}$ is the point where the straight line from the starting position $\mathbf{p}(0)$ to the target centre intersects the target boundary. Time in target measured the duration for which the cursor was within the target during the task. Overshoot was the number of exits from the target during the task. Target variance was defined as:

$$\text{Target positional variance } (V_{\text{pos}}) = \sigma_x^2 + \sigma_y^2$$

$$\text{Target variance } (\%) = \frac{A_{\text{cursor}}}{A_{\text{target}}} \times 100 = \frac{\pi \times V_{\text{pos}}}{A_{\text{target}}} \times 100$$

where σ_x^2 and σ_y^2 are the positional variances in the x and y directions for positions once the cursor has reached the target, A_{cursor} is the area of cursor variance and A_{target} is the area of the target.

MVM

For human testing, the coil was taped to the skin over the proximal tibialis anterior magnet. Participants produced 25, 50, 75 and 100% maximum voluntary contraction efforts, yielding 14 trials across two participants with simultaneous iEMG recordings for one of the participants. MVM signals were filtered with a 60-Hz notch and a 10- to 150-Hz Butterworth bandpass filter. Segments were binned into MVC effort windows to calculate the zero crossing frequency within the 3-s movement period. The normalized MVM signals used the zero crossing rate, which was computed across the whole signal using a 200-ms sliding window with a minimum amplitude threshold to exclude baseline noise and a subsequent 10-Hz low-pass Bessel filter. Within each trial, the normalized MVM and EMG signals were averaged across the effort window.

Statistics

Statistical analyses were performed using the Python statistical analysis packages numpy and scipy. The data are presented as means $\pm$ s.e.m. unless otherwise specified. Statistical significance was set at $\alpha = 0.05$, with Bonferroni correction applied for multiple comparisons across interfaces. Before statistical testing, data distributions were assessed using the Shapiro–Wilk test for normality. For unpaired group comparisons, the two-sided Mann–Whitney U test was used. For within-participant comparisons across interfaces, two-sided pairwise Wilcoxon signed-rank tests were performed, paired by experiment condition.

Reporting summary

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

Data availability

All of the data that support the findings of this study are available in the main text or its Supplementary Information. Additional data requests may have restrictions applied due to patient privacy and data-sharing agreements included in the consent forms. Upon institutional review, data that do not violate these restrictions may be available upon reasonable request from the corresponding authors. Source data are provided with this paper.

Code availability

Both the simulation framework to evaluate the tracking algorithms and the information filter algorithm in Python are available on GitHub at <https://github.com/chshallal/Magnet-Tracking-Framework>. Additional code is available upon reasonable request from the corresponding authors.

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Author contributions

C.C.S., C.R.T., R.J.C. and H.M.H. conceived of the MuSE device concept. C.C.S., C.R.T., S.H.Y., R.J.C., D.O., G.H.-A., T.S., J.Q., M.J.C. and H.M.H. contributed to the methodology, specifically relating to clinical implementation of the MuSE system in humans. R.B. and M.J.C. provided clinical consultation and conducted the surgeries with appropriate clinical follow up. C.C.S., C.R.T., S.H.Y., R.J.C. and H.M.H. performed the electronic system design and implementation of the MuSE and INFO tracking algorithm. C.C.S., S.H.Y. and D.O. developed the simulation environment for evaluating magnet tracking. C.C.S., C.R.T., R.J.C., D.O., G.H.-A., J.Q., J.X., D.L., A.R. and S.B. contributed to experimental investigation and data collection in relation to the MuSE in humans. C.C.S., C.R.T., S.H.Y., R.J.C., G.H.-A. and H.M.H. conceived of and validated the MVM concept. C.C.S., C.R.T., D.O. and G.H.-A.

analysed the data and prepared the main figures. C.R.T., S.H.Y., A.L., E.G.C., J.A.P. and H.M.H. devised and validated the magnetometer calibration process. C.C.S. and C.R.T. wrote the original version of the paper. C.C.S., C.R.T., R.J.C., T.S. and H.M.H. edited the paper. H.M.H. provided supervision and funding for the research. All authors reviewed and approved the final version of the paper.

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Competing interests

H.M.H. and M.J.C. are inventors on patents (PCT/US2014/061773 and PCT/US2017/012553) describing AMI amputation, filed by MIT. H.M.H., C.R.T., S.H.Y., R.J.C. and J.Q. are inventors on patents (PCT/US2018/055053, PCT/US2021/056092 and PCT/US2024/040464) describing the MuSE system and techniques, filed by MIT. R.B. is an inventor on a patent (PCT/SE2017/051109) describing osseointegration and the OPRA system, filed by Integrum. The other authors declare no competing interests.

Additional information

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Data collection	Patient data were collected using custom magnetometer arrays, an EMG acquisition platform connected to both surface and implanted electrodes, and a wireless goniometer (Biometrics Ltd., UK). All data streams were digitally synchronized. Magnet tracking simulation environment and neuroprosthetic controllers are publicly available on GitHub (https://github.com/chshallal/Magnet-Tracking-Framework) or in the supplementary material.
Data analysis	Statistical analyses were performed using Python statistical analysis packages such as numpy and scipy.

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All data supporting the findings are available in the main text or the supplementary materials. Relevant code for the magnet tracking algorithm and simulation are

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Reporting on sex and gender

The study involved 2 males and 1 female. Sex was self-reported. As the study was designed to assess neuroprosthetic performance across different interfaces with those who had received a bionic reconstruction at the transtibial amputation level, neither sex nor gender were considered in this study.

Reporting on race, ethnicity, or other socially relevant groupings

No socially constructed or socially relevant categorization variables were collected or analyzed in this study.

Population characteristics

Three participants with transtibial amputation and bionic reconstruction were enrolled. Mean age was 49.0 ± 5.0 years and participants had an average height of 1.74 ± 0.03 m and weight of 82.4 ± 2.7 kg. Further characteristics are included in the supplementary material.

Recruitment

Three participants who satisfied both inclusion and exclusion criteria were recruited to receive the bionic reconstruction. Pre-screening to determine eligibility, surgical implantation, and clinical follow-up were conducted at Mass General Brigham Hospital (Boston, Massachusetts) under Mass General Brigham IRB protocol #2024P000006. Informed written consent for both surgery and human subjects testing was obtained under the Mass General Brigham protocol, to which the MIT IRB ceded review to. Participants provided written consent at both MIT and Mass General Brigham sites prior to surgery and experimental testing. A full detailed list of inclusion and exclusion criteria and study interventions can be found at <https://clinicaltrials.gov/study/NCT06391697>.

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The study protocol was approved by both the U.S. Food and Drug Administration, Mass General Brigham IRB and the MIT IRB.

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No formal power analysis was conducted as this was an early feasibility study. Sample size was determined by availability of eligible participants who met strict inclusion criteria and underwent the surgical procedure. The study incorporated repeated measures as each participant completed multiple trials across varying conditions.

Data exclusions

No data were excluded from the analyses.

Replication

Neuroprosthetic interface assessments showed consistent results and trends across the three different subjects with the bionic reconstruction.

Randomization

Participants were not randomly assigned to groups, as all participants received the same surgical intervention and completed all experimental conditions. Within experimental tasks, target locations and conditions were presented in randomized order.

Blinding

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Study protocol	https://clinicaltrials.gov/study/NCT06391697
Data collection	All data were collected both at Massachusetts Institute of Technology and Brigham and Women's Hospital. The period of recruitment and data collection was from 2023 to 2025.
Outcomes	We assessed neuroprosthetic performance across all three interfaces using two measures: (1) accuracy of joint kinematics reconstruction from residual limb signals, and (2) multi-degree-of-freedom cursor control in a virtual ankle-subtalar movement task.

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Seed stocks	N/A
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