

RESEARCH ARTICLE OPEN ACCESS

T-800: An 800 Hz Data Glove for Precise Hand Gesture Tracking

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Received: 4 February 2026 | **Revised:** 6 May 2026 | **Accepted:** 22 May 2026

Keywords: data glove | dexterous manipulation | high-frequency motion | kinematic retargeting | multi-IMU synchronization

ABSTRACT

Human dexterity relies on rapid, sub-second motor adjustments, yet capturing these high-frequency dynamics remains an enduring challenge in biomechanics and robotics. Existing motion capture paradigms are compromised by a trade-off between temporal resolution and visual occlusion, failing to record the fine-grained hand motion of fast, contact-rich manipulation. Here we introduce T-800, a high-bandwidth data glove system that achieves synchronized, full-hand motion tracking at **800 Hz**. By integrating a novel broadcast-based synchronization mechanism with a mechanical stress isolation architecture, our system maintains sub-frame temporal alignment across 18 distributed inertial measurement units (IMUs) during extended, vigorous movements. We demonstrate that T-800 recovers fine-grained manipulation details previously lost to temporal undersampling. Our analysis reveals that human dexterity exhibits substantial motion energy components above 100 Hz that was inaccessible due to the Nyquist sampling limit imposed by previous hardware constraints. To validate the system's utility for robotic manipulation, we implement a kinematic retargeting algorithm that maps T-800's high-fidelity human gestures onto dexterous robotic hand models. These experiments demonstrate that the high-frequency motion data can be accurately translated while respecting the kinematic constraints of robotic hands, providing the rich behavioral data necessary for training robust control policies in the future.

1 | Introduction

The human hand is a marvel of evolution, capable of executing sub-second, high-precision motor adjustments that remain unmatched by artificial systems. Advances in high-DoF robotic hands have brought machines closer to this level of dexterity [1–5], enabling potential applications in minimally invasive surgery [6, 7], precision assembly [8, 9], unstructured household environments [10–12], and so on. However, the mechanical

sophistication of these platforms introduces a control bottleneck: coordinating dozens of actuators in real-time to generate natural, agile behavior.

With the advances in deep learning, data-driven imitation learning has emerged as a promising solution by utilizing human demonstrations to guide robots through complex action spaces [13–17]. Consequently, the fidelity of the recorded

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human motion datasets establishes an *upper bound* on robotic performance [18]. To reproduce the agility of a human hand, a system must capture the full spectrum of motion—particularly the high-frequency dynamics (> 100 Hz) that characterize rapid manipulation and contact responses [19].

Despite this critical need, current motion capture technologies face a fundamental dilemma between temporal resolution and spatial reliability. Optical systems (e.g., Vicon [20]) offer high sampling rates but suffer from severe occlusion during object interaction—precisely the moments when accurate tracking is most critical. Conversely, wearable inertial measurement unit (IMU)-based approaches allow for occlusion-free capture but are historically plagued by two limitations. First, sampling rates rarely exceed 200 Hz [21–25], failing to satisfy the Nyquist sampling theorem for capturing rapid transient motions without aliasing. Second, independent sensor clocks drift over time, causing temporal misalignment that disperses simultaneous joint synergies across different timestamps. This temporal blurring degrades data integrity, rendering it unsuitable for learning precise dynamic models (Table 1 provides a detailed comparison of representative state-of-the-art IMU-based hand motion capture systems).

To bridge this gap, we present T-800, a high-frequency full-hand tracking system designed to capture the previously overlooked dynamics of human dexterity. As illustrated in Figure 1, T-800 integrates a compact 18-node IMU array with a reconfigurable communication protocol to achieve online-synchronized 800 Hz acquisition. Unlike prior systems that rely on kinematic priors to hallucinate full-hand pose from fingertip IMU readings [24, 25, 27, 32], or from flex sensor data [26, 28, 30], our system directly measures all finger segments. By quadrupling the bandwidth of conventional data gloves and enforcing sub-frame synchronization, T-800 provides a new opportunity to observe and analyze the high-speed spectral content of human manipulation.

Our primary contributions are.

- **High-Frequency Full-Hand Capture:** We develop a flexible glove architecture that achieves 800 Hz tracking across 18 joints. A novel mechanical isolation design (“sandwich structure”) ensures normal operation of the internal IMU while preserving natural hand dexterity.
- **Broadcast-Based Temporal Calibration:** We introduce a synchronization protocol that eliminates clock drift. By broadcasting a global timestamp latch command, we maintain sub-frame alignment across all distributed sensors throughout extended recording sessions.
- **Spectral Analysis of Dexterity:** Our system reveals that rapid hand–object interactions (e.g., pen spinning) contain substantial energy information above 100 Hz, suggesting that traditional 200 Hz systems undersample human agility.
- **Kinematic Retargeting:** We implement a geometric retargeting algorithm to map high-speed human hand data to dexterous robotic hand models, validating the kinematic compatibility of the capture data and laying the data foundation for future robust control algorithm training.

The remainder of this article is organized as follows. We begin by detailing the system architecture in Sec. 2.1, including the

wearable platform design and mechanical isolation strategy. We then present our core algorithmic contributions: a broadcast-based synchronization protocol that eliminates clock drift (Section 2.2) and a spatial calibration framework for anatomical alignment (Section 2.3). In Section 2.4, we validate the system's high-frequency capture capabilities through spectral analysis of rapid hand–object interactions. Section 2.5 presents our kinematic retargeting framework and analyzes the mapping performance on robotic hand models. Finally, Section 3 summarizes our findings and discusses future research directions, with comprehensive implementation details—including fabrication, hardware, and firmware specifications—provided in Section 4.

2 | Results and Discussion

2.1 | T-800 System Overview

As illustrated in Figure 1, the T-800 system is engineered to mitigate the trade-off in wearable motion capture: achieving high-fidelity, high-frequency kinematic tracking while imposing negligible physical restriction on natural hand dexterity. The system architecture integrates three tightly coupled subsystems: a mechanically isolated wearable sensing platform, a low-inertia wrist-mounted hub, and a real-time spatiotemporal reconstruction pipeline.

The wearable component (Figure 1a), or the data glove, features a flexible glove substrate tailored to the complex anatomical curvature of the human hand (fabrication details in Section 4.1). To capture all DoFs of the human hand, the system employs 18 distributed IMU islands. A critical innovation in our design is the miniaturized IMU island, measuring just 9.8 mm in length, 6.8 mm in width, and 2.2 mm in height. This ultra-compact form factor is specifically optimized to minimize inter-finger interference and proprioceptive obstruction during fine manipulation tasks. Furthermore, the island features a novel mechanical architecture designed to address the persistent challenge of firm sensor-to-bone coupling, as skin deformation and fabric sliding typically decouple sensors from underlying bone movement.

As depicted in the exploded and cross-sectional views of Figure 1b,c, each IMU island utilizes a “sandwich structure.” A custom metal top shield and a bottom support plate form a rigid exoskeleton that mechanically encapsulates the central IMU. This configuration creates a stress-shielding effect: tension forces exerted by the glove fabric (blue arrows) and reaction forces from the phalanges (purple arrows) are routed through the rigid outer housing, effectively bypassing the sensing element. Consequently, the IMU remains mechanically decoupled in the center, protected from shear stresses and pressure concentrations that would otherwise induce measurement errors. Simultaneously, this rigid interface concentrates the normal force to generate sufficient friction, ensuring firm, nonslip coupling between the sensor and the finger bone even during high-velocity movements.

The distributed sensor array is interconnected via a network of five custom-designed flexible printed circuits (FPCs) that conform to the hand's varying geometry. Unlike standard cabling, each FPC segment is geometrically optimized for the

TABLE 1 | Comparison of different hand motion capture systems with IMU-based sensing.

Name	Sensor type	IMU type	Connectivity	Haptic obstruction	Synchronization	Palm & arm sensors ↑	Finger sensors ↑	IMU count ↑	Sample rate (Hz) ↑
iSEG-Glove [21]	IMU	MPU9150	Wi-Fi	Fully-obstructed	No	1	3	16	40
M. Edmonds et al.. [22]	IMU	BNO055	Wired	Fully-obstructed	No	1	3 (2 for thumb)	15	20
G. Saggio et al.. [23]	IMU	MPU9250	Wired	Cutout rings	No	3	3	18	40
Z. Yang et al.. [24]	IMU + magnetic	MPU9250	Wired	Fingertip	Post-process	1 + 0	1 + 1	3	100
FI-HGR [25]	IMU + flex	ICM20948	Bluetooth	Fully-obstructed	Post-process	1 + 0	1 + 0 (1 + 1 for index)	6	50
M.A. Ahmed et al.. [26]	IMU + flex	MPU9250	Bluetooth	Fully-obstructed	No	1 + 1	1 + 1	6	—
C. Lu et al.. [27]	IMU	ICM20948	Wi-Fi	Finger dorsal	Post-process	2	3	5	200
HIMT [28]	IMU + flex	BNO085	Wi-Fi	Fully-obstructed	Post-process	2 + 0	0 + 1	2	—
ASTRA [29]	IMU	MPU9250	Wired	Fully-obstructed	Post-process	1	3	16	100
L. Fan et al.. [30]	IMU + flex	MPU6050	Bluetooth	Fully-obstructed	No	1 + 0	0 + 1	1	—
B. Lin et al.. [31]	IMU	LSM9DSO	Bluetooth	Fully-obstructed	No	2	3	17	25
C. Lu et al.. [32]	IMU	ICM20648	Bluetooth	Fully-obstructed	No	1	1	6	200
Metagloves Pro [33]	IMU + magnetic	—	BLE	Palm & fingertip	—	1 + 0	1 + 1	6	120
TI-Glove [34]	IMU + flex	MPU9250	Wi-Fi	Fully-obstructed	No	1 + 0	0 + 1	1	100
T-800 (This work)	IMU	BHI360	Wi-Fi	Cutout rings	Online	3	3	18	800

Note: An upward arrow indicates that higher values are better. The bold values indicate the best values.

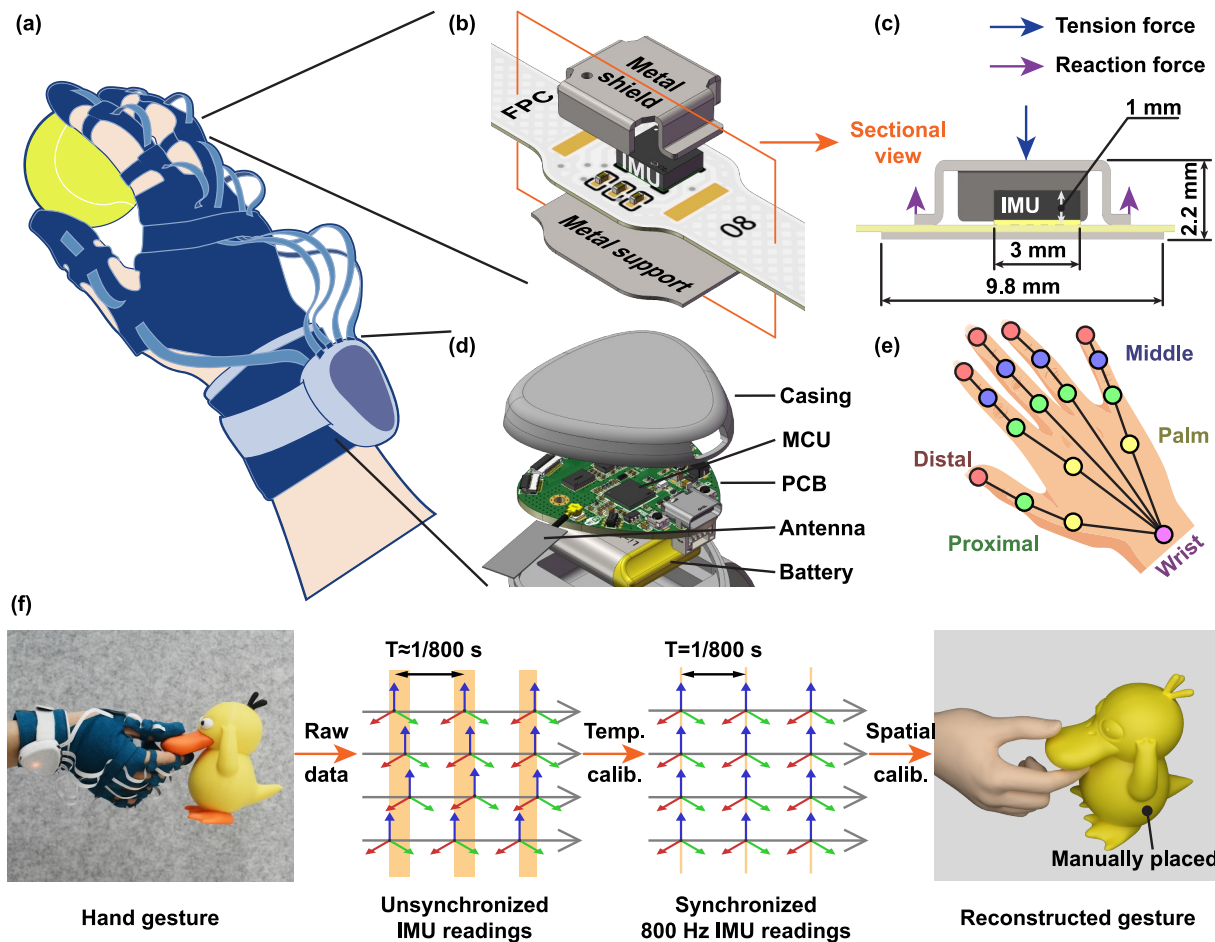


FIGURE 1 | System architecture and processing pipeline of the T-800 high-frequency tracking system. (a) The wearable platform features an anatomically aligned, flexible sensor array designed to minimize restriction on natural hand movements. (b–c) Mechanical isolation strategy. (b) Exploded and (c) cross-sectional views of the “sandwich structure.” The rigid metal shield and support plate mechanically decouple the sensor from the fabric and skin; tension forces (blue arrows) and bone reaction forces (purple arrows) are routed through the rigid housing, ensuring stable coupling. (d) Wrist-mounted sensor hub consolidating heavy components (battery, MCU) to minimize inertial loading on the finger segments. (e) Topology of the 18-sensor array covering the full kinematic chain. (f) Spatiotemporal reconstruction workflow. The pipeline transforms raw, asynchronous, and drifting data streams into a coherent 800 Hz signal via broadcast-based temporal calibration, followed by spatial alignment to reconstruct high-fidelity gestures (visualized via the MANO model [35]).

specific range of motion of its corresponding joint—from the proximal knuckles to the distal fingertips. This design ensures that the interconnects possess sufficient compliance to accommodate full flexion without constraining joint mobility, yet remain taut enough to prevent excessive slack that could introduce sensor displacement. The specific material composition and layout of these flexible stripes are further detailed in Section 4.2.

To minimize the kinetic impact on hand dynamics, the T-800 design strategically consolidates all substantial mass components—including the microcontroller unit (MCU), battery, wireless antenna, and main printed circuit board (PCB)—into a single wrist-mounted sensor hub (Figure 1d). By shifting the center of mass away from the distal segments to the wrist, this design substantially reduces the mass and inertia loaded onto the fingers, thereby preserving the user's natural agility during dynamic motions. The hub creates a protective enclosure for the electronics while serving as the central aggregation point for the

distributed array. Hardware specifics of the sensor hub are provided in Section 4.3.

The sensor hub interfaces with 17 IMU islands via the five FPCs, with an 18th reference IMU embedded directly within the hub itself. The sensor topology is organized to align with the skeletal structure of the hand (Figure 1e), with each FPC branch hosting 3–4 nodes corresponding to the metacarpal and phalangeal bones of a single digit (color-coded from yellow to red). This comprehensive coverage ensures the capture of the complete kinematic chain from the wrist to the fingertips, leaving no joint unmeasured.

The end-to-end operation workflow is visualized in Figure 1f. The system operates as a distributed network where each IMU independently samples orientation data asynchronously at a nominal rate of 800 Hz. These raw, unsynchronized data streams, along with their local timestamps, are transmitted wirelessly to a host computer for real-time processing. To recover a coherent

kinematic model from these independent streams, the host executes a two-stage calibration pipeline.

2.1.1 | Temporal Calibration

Addressing the stochastic nature of independent sensor oscillators, this stage applies our broadcast-based synchronization algorithm (detailed in Section 2.2). It aligns the drifting local time bases of all 18 sensors to a unified global reference, effectively interpolating the irregular asynchronous samples into a strictly synchronized 800 Hz grid (Figure 1f).

2.1.2 | Spatial Calibration

To account for the inevitable physical variations in sensor placement, this stage computes the transformation between each IMU's local frame and its corresponding anatomical bone frame using data collected during an initialization procedure (detailed in Section 2.3).

The final output is a high-fidelity, synchronized motion dataset where the orientation of every hand segment is expressed in a consistent world reference frame. This calibration pipeline facilitates the accurate reconstruction of complex interactions, such as the grasping demonstrated in Figure 1f.

2.2 | Multi-IMU Synchronization

Achieving precise temporal coherence across a distributed sensor array represents a challenge in wearable computing. In compact systems lacking dedicated synchronization lines, conventional architectures rely on the MCU to sequentially poll individual nodes (Figure 2a). This method suffers from a fundamental hardware limitation: each IMU operates on an independent internal oscillator. Due to manufacturing mismatches and temperature variations, these oscillators exhibit stochastic frequency deviations. This translates to a nominal offset from 800 Hz along with an unpredictable fluctuation in the sampling rate. These minute frequency discrepancies integrate over time, causing the local clocks to diverge gradually (Figure 2b). Even with an initial one-time calibration, this accumulated drift inevitably results in millisecond-scale misalignment during extended recordings, destroying the temporal integrity of rapid, coordinated hand movements.

To eliminate this drift, the T-800 system implements a novel synchronization protocol built upon a reconfigurable communication architecture. Beyond standard one-to-one transactions, we programmed the MCU's I/O matrix to support a hardware-level broadcast mode (Figure 2c). In this mode, a single capture-timestamp command is transmitted simultaneously onto the data lines and chip selection lines of all IMUs through the I/O matrix. Upon command arrival, every sensor latches its current local timestamp. These globally synchronized events serve as absolute temporal anchors (Figure 2d). The host computer utilizes these anchors to reconstruct a unified global timeline (implementation details in Section 4.4). By modeling the relationship between each sensor's local clock and the master clock as a series of piecewise-linear segments constrained by successive broadcast anchors, the algorithm dynamically compensates for time-varying frequency drift. This

allows the asynchronous raw data streams to be interpolated onto a strictly aligned 800 Hz grid with sub-frame precision.

The necessity of this approach is validated through a high-velocity hand-flipping experiment (Figure 2e). Figure 2f quantifies the temporal evolution of the 18 sensor clocks under standard one-time calibration; the time offsets exhibit divergence over a 140 s session. Such clock drift manifests as severe temporal divergence in the reconstructed motion. As shown in Figure 2h, the residual clock skew causes accumulated errors in the recorded motion, where the fingers appear to flip asynchronously despite being in a uniform motion. In contrast, our broadcast-based calibration maintains a tight, bounded error distribution throughout the session. The resulting reconstruction (Figure 2i) preserves the temporal fidelity of the motion, ensuring that the kinematic phases of all fingers are aligned—a prerequisite for analyzing the high-frequency dynamics of dexterity.

2.3 | Full-Hand Gesture Reconstruction

Transforming raw inertial measurements into a coherent biomechanical model requires the mapping from the sensor's arbitrary mounting frame to the anatomical joint frame. We derive a rigorous two-step framework to calibrate this mapping by leveraging gravity vectors and physical constraints.

2.3.1 | Notation and Frames

We employ the notation $R_i^j \in SO(3)$ to denote the rotation matrix that transforms frame $\{i\}$ to frame $\{j\}$. Our calibration process involves four principal coordinate frames, as illustrated in Figure 3: the world frame $\{W\}$, the IMU world frame $\{IW\}$, the hand frame $\{H\}$, and the IMU body frame $\{I\}$.

The IMU world frame $\{IW\}$ is established at sensor initialization and remains fixed thereafter. A key property of $\{IW\}$ is that its z -axis aligns antiparallel to the gravity vector, as determined during initialization. The rotation R_I^{IW} represents the current IMU orientation measurement with respect to this initial frame. Without loss of generality, we define the world frame $\{W\}$ such that its z -axis also opposes gravity. Under this definition, frames $\{W\}$ and $\{IW\}$ differ only by a rotation θ about their common z -axis, yielding the rotation matrix

$$R_{IW}^W = \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}. \quad (1)$$

2.3.2 | Problem Formulation

Our reconstruction objective is to recover the anatomical hand orientation R_H^W given the instantaneous sensor measurement R_I^{IW} . The kinematic chain is governed by the general transformation:

$$R_H^W = R_{IW}^W R_I^{IW} R_H^I. \quad (2)$$

This equation contains two unknown static transformations: the global heading offset R_{IW}^W (parameterized by θ) and the bone-to-

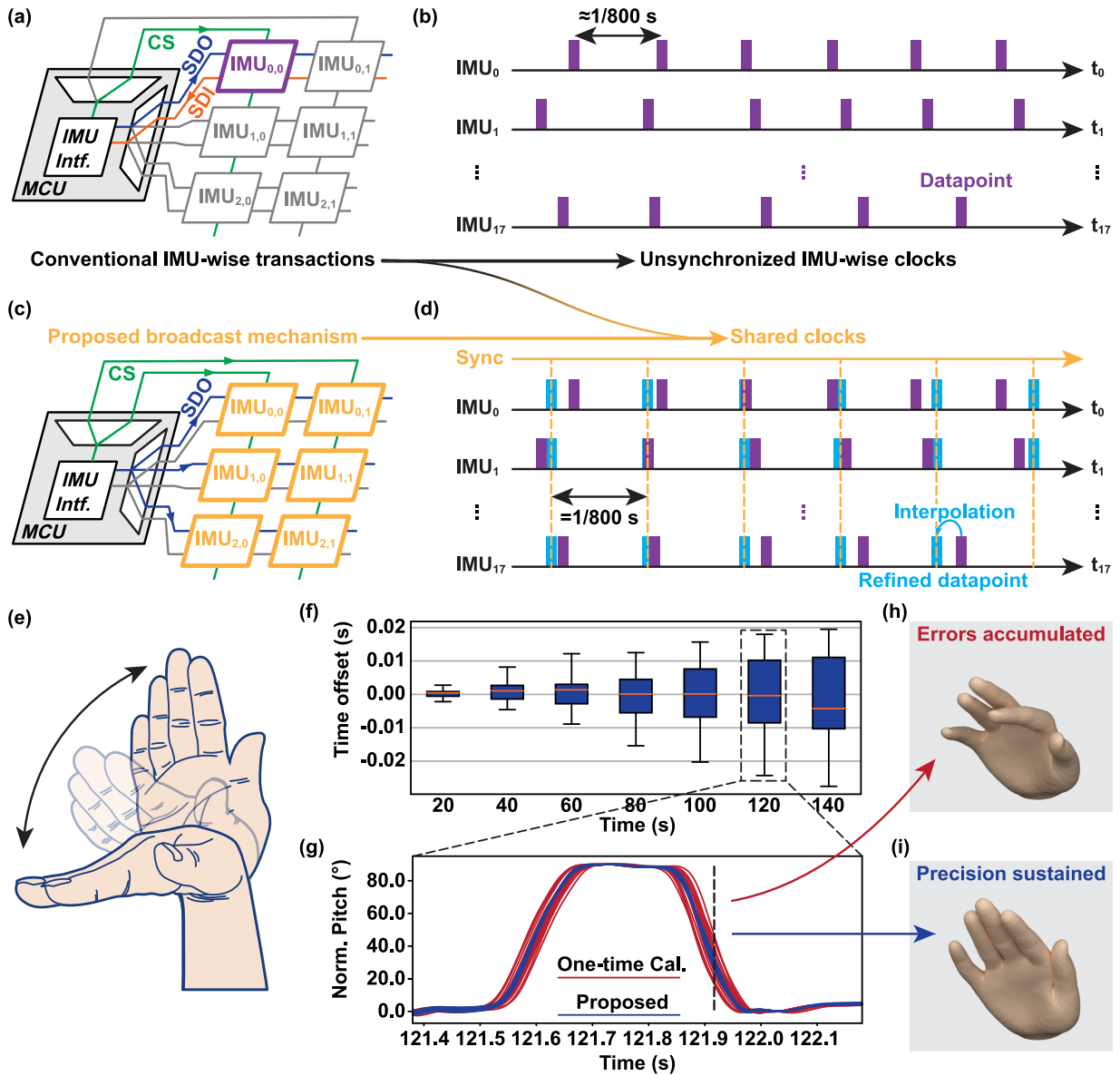


FIGURE 2 | Broadcast-based temporal calibration mechanism for drift-free multi-sensor synchronization. (a–b) The desynchronization bottleneck. (a) Conventional architectures rely on sequential polling of individual nodes. (b) Each IMU runs on an independent internal oscillator. Slight frequency variations accumulate into significant clock drift, causing nominally simultaneous samples to scatter across the timeline (temporal jitter). (c–d) Broadcast synchronization protocol. (c) The proposed architecture utilizes a simultaneous broadcast command to latch a global timestamp across all IMUs instantly. (d) These latched timestamps serve as shared anchor points, enabling the system to interpolate asynchronous raw readings onto a unified, strictly aligned temporal grid. (e–i) Validation via rapid dynamics. (e) A rapid hand-flipping task (140 s duration) serves as a stress test. (f) Quantitative analysis of time offsets reveals diverging clock drift across the 18 sensors using standard one-time calibration. (g) Signal coherence analysis: the proposed method (blue) maintains tight synchronization of finger pitch angles, whereas the baseline (red) exhibits severe temporal divergence. This divergence manifests visually as (h) the drifted hand gesture in the baseline reconstruction, contrasted with (i) the sustained kinematic fidelity and sub-frame precision achieved by our broadcast approach.

sensor mounting orientation R_H^I . We solve for these unknowns via a constraint-based calibration protocol.

Step 1 Zero Pose Calibration

As shown in Figure 3a, we first place the hand flat on a horizontal surface, such as a tabletop, with the palm facing downward. We define the forward direction of the hand as the y-axis of the world frame and designate this configuration as the zero pose:

$$R_{H_0}^W = I, \quad (3)$$

where I denotes the 3×3 identity matrix. Substituting Equation (3) into Equation (2) and recording the corresponding IMU reading $R_{I_0}^W$, we can express R_H^I in terms of $R_{I_0}^W$:

$$R_H^I = R_{I_0}^I R_{I_0}^W R_H^W = R_{I_0}^I R_{I_0}^W. \quad (4)$$

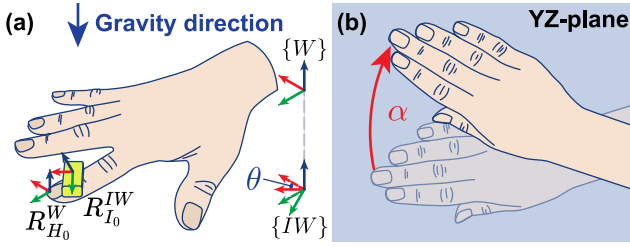


FIGURE 3 | Two-stage framework for calibrating sensor-to-bone mapping. (a) Zero pose calibration: the hand is placed flat on a horizontal surface in the zero pose. The frames W and IW differ only by a rotation θ about their common z -axis (aligned antiparallel to gravity). (b) θ calibration: the hand is rotated by angle α about the world-frame x -axis against a vertical YZ -plane (e.g., a wall). to determine the unknown parameter θ .

This substitution leverages the more tractable form of R_{IW}^W established in Equation (1), reducing our unknowns to the single parameter θ .

Step 2 θ Calibration

To determine θ , we rotate the hand about the world-frame x -axis by an angle $\alpha \in (0, \pi)$, as illustrated in Figure 3b. This rotation can be performed by placing the hand against a vertical YZ -plane, such as a wall. We record the IMU readings at the start and end of this rotation, denoted by $R_{I_s}^{IW}$ and $R_{I_e}^{IW}$, respectively. Leveraging Equation (2), the relationship between these frames can be expressed as

$$R_{I_0}^{IW} R_{I_s}^{IW} R_{I_e}^{IW} R_{I_0}^{IW} = R_W^{IW} R_{H_e}^{H_s} R_{I_0}^{IW}, \quad (5)$$

where $R_{H_e}^{H_s}$ represents the rotation by angle α about the x -axis. For notational simplicity, we denote the known left-hand side as R . Expanding the right-hand side yields

$$R = \begin{bmatrix} \cos \theta & \sin \theta & 0 \\ -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \alpha & -\sin \alpha \\ 0 & \sin \alpha & \cos \alpha \end{bmatrix} \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \\ = \begin{bmatrix} * & * & -\sin \theta \sin \alpha \\ * & * & -\cos \theta \sin \alpha \\ * & * & * \end{bmatrix}, \quad (6)$$

where asterisks denote elements not needed for our solution. Since $\alpha \in (0, \pi)$, we have $\sin \alpha > 0$. By examining the third column, we can directly solve for θ :

$$\theta = \text{atan2}(-R_{13}, -R_{23}), \quad (7)$$

where R_{ij} denotes the element of R in the i -th row and j -th column. With θ determined, both unknown transformations R_{IW}^W and R_H^I are fully specified, completing the calibration procedure.

2.3.3 | Validation

This closed-form solution allows us to simultaneously compute the 18 unique sets of calibration matrices for the entire hand in

a single pass. To validate the kinematic fidelity of this approach, we evaluated the system against the standard 33-grasp taxonomy [36]. As visualized in Figure 4, T-800 accurately reconstructs the full spectrum of human grasp types—ranging from power grasps to precision pinches—without kinematic singularities, confirming that the spatial calibration effectively factorizes out sensor mounting heterogeneity.

2.4 | Spectral Analysis of High-Speed Manipulation

The 18-channel synchronized acquisition capability of T-800, operating at a stable 800 Hz, provides a unique observational window into the spectral composition of human dexterity. By extending the bandwidth limitations of prior hardware, we can now rigorously investigate the high-frequency kinematic information (> 100 Hz) that may exist in the rapid manipulation tasks. To probe this, we subjected the system to a set of dynamic tasks involving fine motor control (pen spinning) and impact absorption (tossing and catching), as visualized in Figure 5.

2.4.1 | Frequency Domain Signal Processing

We quantify the spectral power density of hand motion through a systematic signal-processing pipeline designed to extract transient kinematic features. First, we compute the instantaneous magnitude of the angular velocity vector for each anatomical segment. To localize transient spectral features in the time domain, we apply a short-time Fourier transform (STFT) to the angular velocity signal. We utilize a Hann window of length 256 samples combined with a sliding step size of 16 samples, yielding time-varying energy strength at each frequency point.

Crucially, our analysis isolates spectral energy components strictly exceeding the 100 Hz threshold. This cutoff targets the blind spot of current technology. Since conventional wearable IMU systems typically operate at sampling rates below 200 Hz, their signal reconstruction capacity is mathematically hard-capped at 100 Hz by the Nyquist sampling theorem. The energy in > 100 Hz components observed by T-800 provides evidence that rapid manipulation can generate measurable high-frequency inertial content that is outside the reconstructable band of 200 Hz acquisition.

2.4.2 | Biomechanical Energy Profiles

The resulting energy landscapes, plotted as the linear summation of high-frequency components (> 100 Hz) (without logarithmic scaling to emphasize differences) in Figure 5b,e, reveal that human dexterity exhibits rich spectral content well beyond the sampling limits of previous hardware.

In the precision manipulation task involving counterclockwise pen spinning (Figure 5b), which recruits the thumb, index, and middle fingers, we observe sharp, distinct bursts of high-frequency energy. These bursts are spatially localized exclusively to the three manipulating digits, appearing in temporal synchrony with the rapid actuation phases required to maintain object rotation. Extending this to a bidirectional task, (Figure 5c) introduces additional high-frequency signatures,

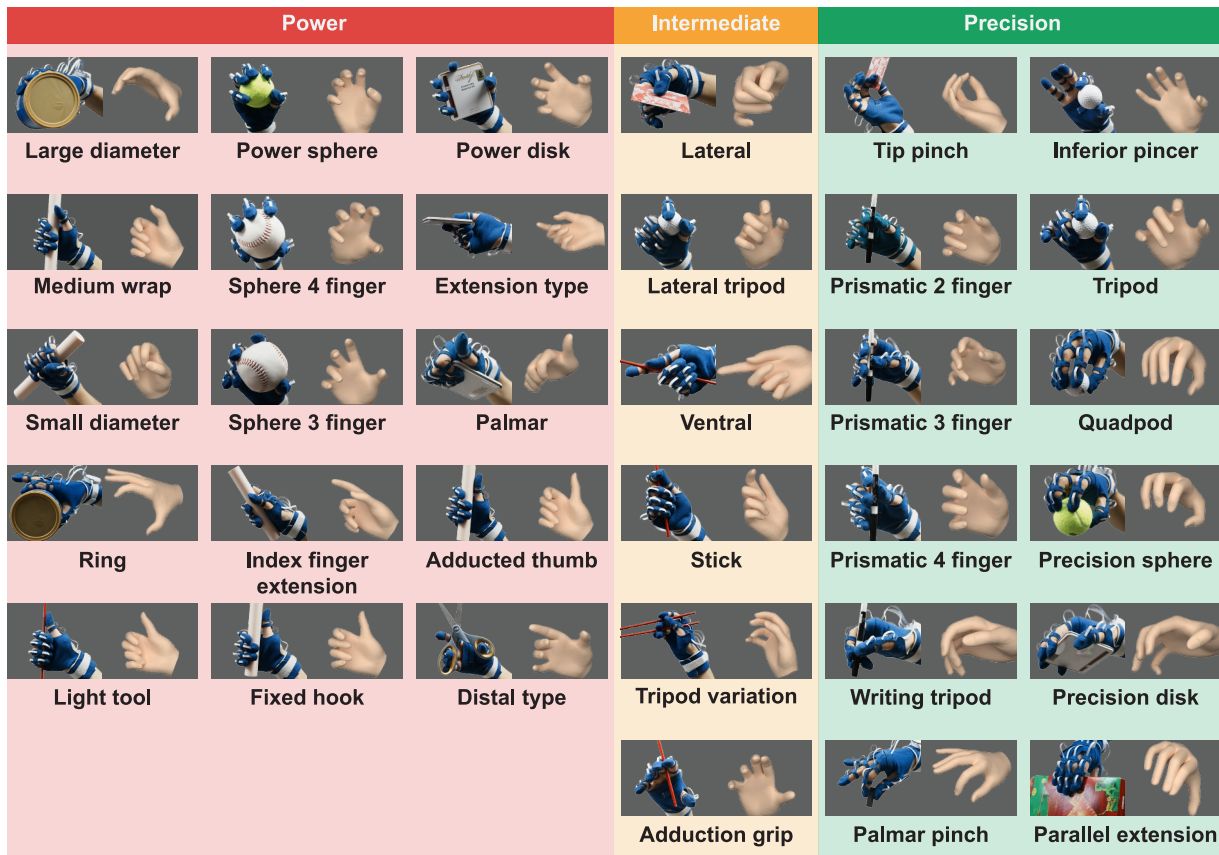


FIGURE 4 | Validation of kinematic fidelity across the 33-grasp taxonomy. Systematic evaluation comparing physical hand configurations (left columns) with real-time reconstructions (right columns) captured by T-800. The dataset is stratified according to the Feix et al. taxonomy [36] into three biomechanical categories: Power grasps (red) requiring high-force closure involving the palm, Intermediate grasps (yellow) balancing active manipulation with stability, and Precision grasps (green) demanding fine-grained fingertip articulation. The consistent reconstruction accuracy across this diverse range confirms two critical system properties: (i) the mechanical design preserves the hand's natural kinematic workspace without perceptible impedance; and (ii) the spatial calibration framework remains robust across the entire manifold of human hand poses.

corresponding to the complex rapid deceleration and re-acceleration required to reverse the pen's angular momentum.

We further showed a four-finger spinning task that explicitly excludes the thumb (Figure 5d). The resulting energy profile demonstrates intense spectral activation across the index, middle, ring, and pinky fingers, as well as the palm. In stark contrast, the thumb and forearm segments remain spectrally quiescent (exhibiting a flat energy response). This negative control confirms that the observed high-frequency signals originate from hand-object manipulation, rather than sensor noise or mechanical resonance propagated globally through the glove structure.

Finally, in the heavy softball tossing task (Figure 5e), the system captures the phase of impact absorption. Unlike the localized finger dynamics of pen spinning, this task elicits a synchronized, high-energy response across the entire hand (excluding the lower arm) as the fingers and palm work in unison to absorb the ball's impact.

2.4.3 | Insights Into Dexterous Manipulation

These results collectively demonstrate two key insights. First, dexterous hand motions contain rich high-frequency components above 100 Hz that are beyond the reach of existing motion

capture systems. Second, T-800's high sampling rate and synchronized multi-sensor design enable precise localization of these high-frequency components to specific fingers and hand segments involved in the manipulation. This selective activation pattern validates both the spatial accuracy of our calibration and the temporal fidelity of our capture system, opening new possibilities for understanding and analyzing complex hand motions.

The observed > 100 Hz components provide evidence that rapid manipulation can generate measurable high-frequency inertial content that is outside the reconstructable band of 200 Hz acquisition. Although the spatially selective activation patterns reduce the likelihood of purely global noise or whole-glove resonance, the present experiments do not fully exclude local structural vibration, contact-shock artifacts, or processing-parameter sensitivity. Therefore, these spectral results are interpreted as evidence of high-frequency manipulation-associated content, not as definitive proof that all > 100 Hz energy arises from voluntary joint kinematics.

2.5 | Kinematic Retargeting to Robotic Hands

To validate the kinematic compatibility of the captured high-frequency data with robotic systems, we devise a retargeting

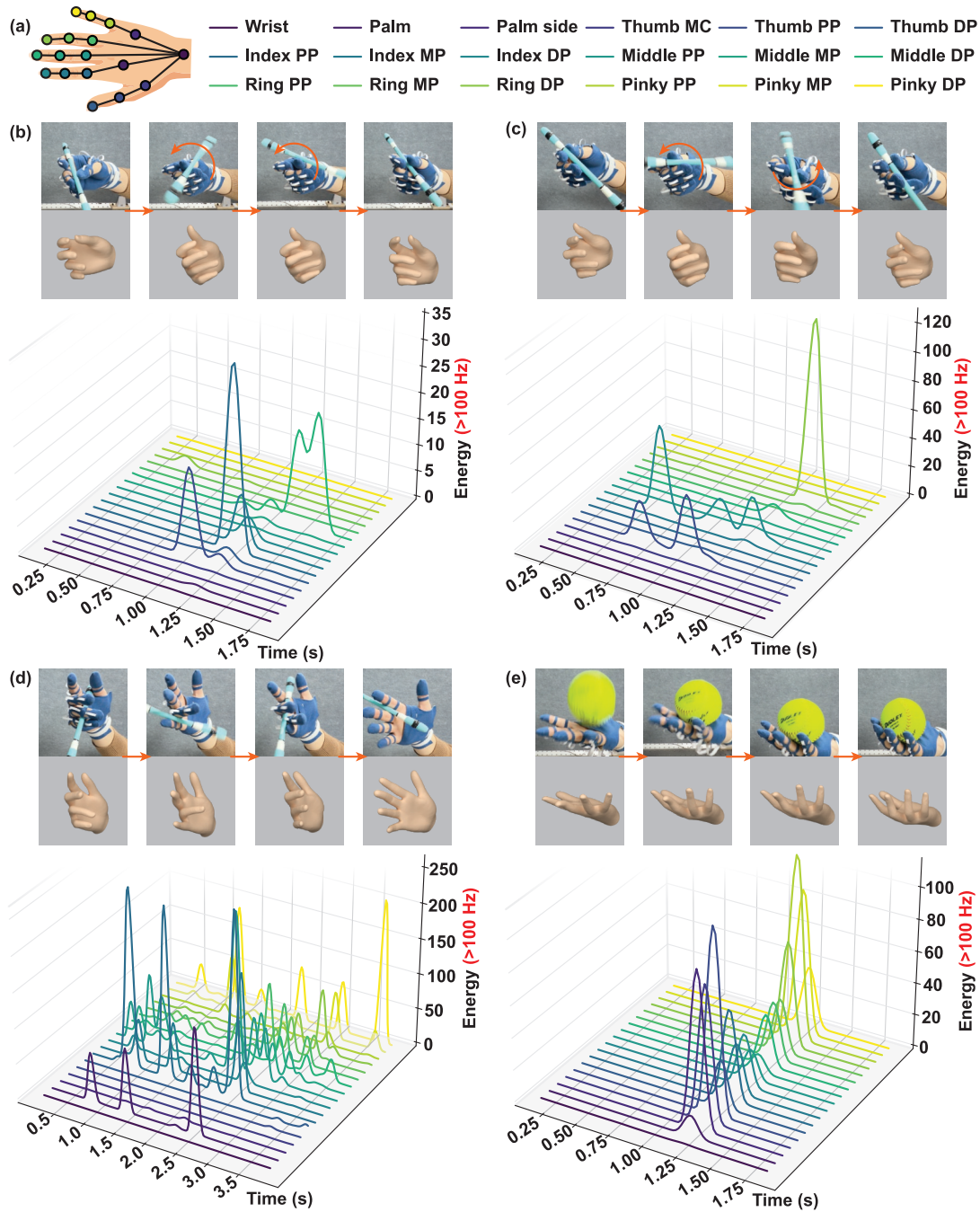


FIGURE 5 | Spectral discovery of high-frequency kinematics in human dexterity. (a) Anatomical sensor mapping of the 18-node array (MC: metacarpal, PP: proximal, MP: middle, DP: distal phalanx). (b–e) Biomechanical energy landscapes. Time-resolved spectral power summation for frequencies strictly > 100 Hz—a band theoretically invisible to conventional 200 Hz systems. (b–c) Pen spinning tasks (unidirectional and bidirectional) reveal distinct, high-amplitude spectral bursts spatially localized to the manipulating digits (Thumb, Index, Middle). These transient spikes coincide with rapid actuation phases, confirming the existence of manipulation-associated high-frequency components that lie beyond the capabilities of previous hardware. (d) In a four-finger spinning task explicitly excluding the thumb, the thumb sensor exhibits spectral quiescence (flatline). (e) Catching a heavy object elicits a synchronized, global high-frequency response across the entire hand. Together, these profiles validate that signal energy > 100 Hz is kinematic information essential for high-fidelity modeling. Detailed manipulation processes and reconstructed gestures are available in the <https://vimeo.com/1148283536/42db8160dd>.

algorithm that maps human hand motion to a dexterous robotic hand model. The objective is to compute the optimal robot joint configuration $\mathbf{q} \in \mathbb{R}^d$ that minimizes the Euclidean distance between key kinematic features of the human and robotic hands, relative to their respective wrist frames.

2.5.1 | Problem Formulation

We formulate this as a constrained optimization problem. For each finger f , we designate the objective as the fingertip position $\mathbf{p}_f$ to ensure manipulation precision. Let $\mathbf{p}^*$ denote the target position derived from the T-800 glove data and $\mathbf{p}(\mathbf{q})$

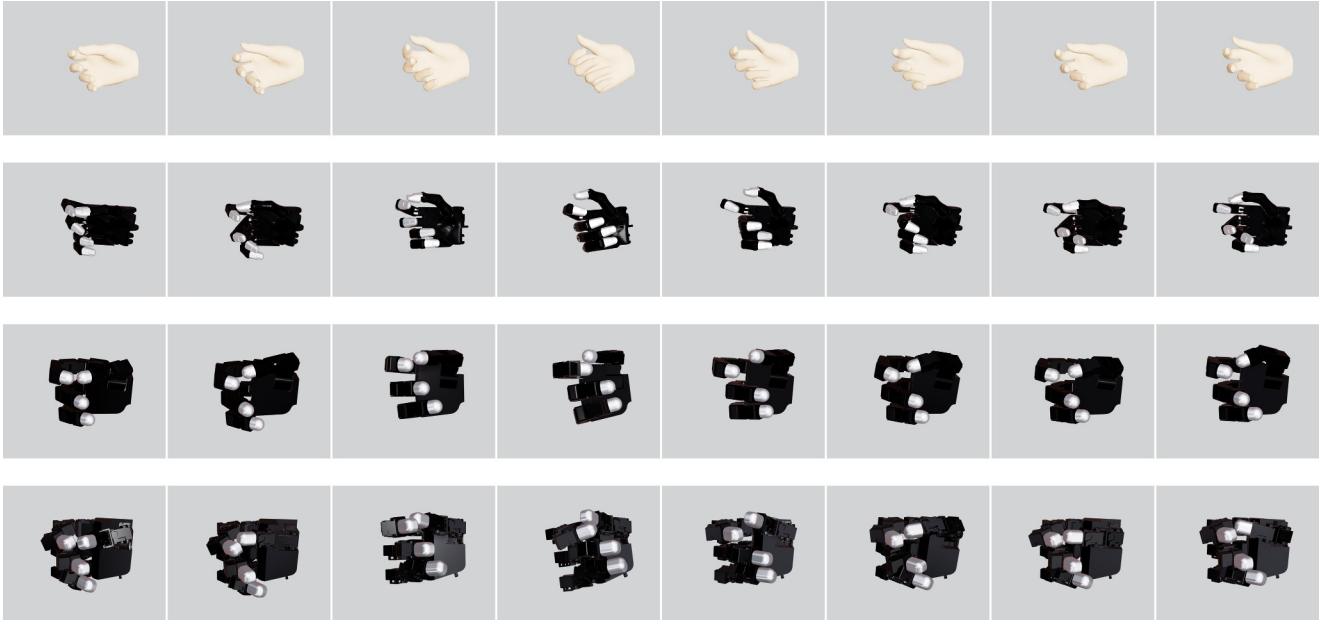


FIGURE 6 | Kinematic retargeting validation across diverse robotic hand platforms. Representative frames from dynamic manipulation tasks demonstrating the mapping of captured human hand motions by T-800 (top row) to three robotic hand models with progressively diverse kinematic structures: Shadow Dexterous Hand, Allegro Hand, and Leap Hand. The sequential frames illustrate the algorithm's ability to transfer high-frequency human manipulation dynamics to robotic platforms while respecting their kinematic constraints.

denote the position computed via the robot's forward kinematics. To solve for the joint updates, we treat the instantaneous tracking error as a vector $\mathbf{e} \in \mathfrak{se}(3)$ within the Lie algebra of the rigid body transformation group. The retargeting problem is formulated as:

$$\begin{aligned} \min_{\mathbf{q}} \quad & \sum_{f=1}^{N_f} \|\Lambda \mathbf{e}_{t,f}(\mathbf{q})\|_2, \\ \text{s.t.} \quad & \mathbf{q}_l \leq \mathbf{q} \leq \mathbf{q}_u \end{aligned} \quad (8)$$

where N_f is the number of fingers, and $\Lambda \in \mathbb{R}^{6 \times 6}$ is a diagonal selection matrix with the first three elements set to one and the remainder to zero, effectively isolating the translation component of the twist. The terms $\mathbf{q}_l$ and $\mathbf{q}_u$ represent the lower and upper joint limits of the robotic hand, respectively.

2.5.2 | Sequential Programming

To solve this nonlinear optimization efficiently, we linearize the forward kinematics around the current configuration $\mathbf{q}$ via the first-order approximation $\Delta \mathbf{p} \approx \mathbf{J}_e \Delta \mathbf{q}$, and apply a sequential programming framework [37, 38]. This approach iteratively refines the solution while adaptively adjusting the step size based on the linear model's approximation quality and the satisfaction of joint constraints.

We derive the effective task Jacobian $\mathbf{J}_e$ via a chain rule that relates changes in joint space to changes in the Lie algebra error vector. This composition involves the standard frame Jacobian $\mathbf{J}(\mathbf{q})$, which maps joint velocities to the end-effector frame pose $E \in \text{SE}(3)$, and the right derivative $\mathbf{J}(E)$ of the logarithmic map, which relates the pose to the Lie algebra error coordinate:

$$\mathbf{J}_e = \Lambda \mathbf{J}(E) \mathbf{J}(\mathbf{q}). \quad (9)$$

2.5.3 | Validation

To verify the versatility of the proposed framework and the kinematic compatibility of the T-800 data, we evaluated the retargeting algorithm on three distinct robotic hands with progressively diverse kinematic structures: the five-finger Shadow Dexterous Hand [4] (24 DoFs), the four-finger Allegro Hand [5] (16 DoFs), and the four-finger Leap Hand [2] (16 DoFs). This selection spans a spectrum from highly anthropomorphic designs to more constrained, lower-degree of freedoms (DoFs) architectures, rigorously testing the algorithm's ability to accommodate substantial kinematic disparities.

We applied the retargeting algorithm to dynamic human manipulation tasks captured in Section 2.4, with representative frames illustrated in Figure 6. Performance was quantified using root mean squared error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{3N_f} \sum_{f=1}^{N_f} \|\Lambda \mathbf{e}_{t,f}(\mathbf{q})\|_2^2}. \quad (10)$$

The results demonstrate precise motion transfer across all platforms, with performance closely correlating to kinematic capabilities. Paradoxically, the Shadow Hand, despite having the closest anatomical correspondence to the human hand, achieved the highest RMSE ((8.3 ± 6.8) mm). This is primarily because its compact design constrains the range of motion for each DoF. In contrast, the Allegro Hand and Leap Hand achieved competitive performance ((1.0 ± 1.8) mm, and (0.6 ± 1.4) mm, respectively), despite their four-finger configuration introducing significant kinematic mismatch. Their superior performance stems from two key factors: larger DoF ranges and the optimizer's ability to exploit redundant joint null spaces to compensate for the anatomical differences.

The retargeting results confirm that the captured hand kinematics can be mapped to representative robot embodiments under their joint limits, demonstrating direct kinematic compatibility for controlling diverse robotic platforms.

3 | Conclusion and Outlook

In this work, we have bridged the gap between high-speed kinematic capture and unhindered human dexterity with T-800, a rapid full-hand tracking system that extends the bandwidth limitations of prior IMU-based systems. By fusing a stress-shielding mechanical architecture with a broadcast-based synchronization protocol, we achieved continuous, drift-free motion tracking at 800 Hz across 18 anatomical joints. Crucially, this system allowed us to empirically uncover the spectral richness of human manipulation, revealing that significant energy exists beyond 100 Hz in fine motor tasks like precision spinning and impact absorption, which lies outside the Nyquist limit of previous hardware. These high-frequency dynamics—previously masked by frequency aliasing—are shown to be carrying valuable information in fine motor tasks like precision spinning and impact absorption.

The implications of T-800 extend beyond biomechanical analysis to serve as an infrastructure for embodied intelligence. By providing a source of occlusion-free, high-fidelity human demonstrations, this platform addresses the data quality bottleneck in robotic imitation learning. Algorithms trained on this kinematic data can potentially acquire agile behaviors that were previously unlearnable due to signal smoothing [13–16, 39]. A controlled comparison of policies or controllers trained from native 800 Hz data and downsampled data is left for future work.

Looking forward, the natural evolution of this platform lies in the convergence of kinematics and kinetics. Integrating dense tactile sensing arrays into the glove structure presents a compelling frontier: coupling spatiotemporal contact maps with our synchronized high-speed motion data would capture the complete sensorimotor loop of human manipulation. Such multimodal datasets are essential for learning bidirectional mappings between tactile feedback and motor control, grounding robotic policies in the physics of contact [40–43]. Additionally, incorporating other sensing modalities, such as triboelectric sensing and sEMG [34, 44], could enhance the accuracy and robustness of the overall system. Ultimately, through open-source hardware benchmarks and standardized data formats, we envision T-800 serving as a foundational tool to catalyze the community's transition from quasi-static grasping to truly dynamic, human-like dexterity.

4 | Methods

4.1 | Fabrication of the Wearable Platform

The wearable substrate is constructed from high-elasticity polyester fabrics, selected for their durability and conformability. The architecture features a dorsal backbone tailored to the hand's topology, extended by a palmar strap that anchors the two palm sensors. To ensure robust sensor-to-bone coupling without adhesives, we implemented a tension-based fixturing mechanism. Elastic rings (positioned at the proximal and

intermediate phalanges) and fingertip caps are manufactured to approximately 90% of the average human's corresponding finger diameter. This intentional undersizing induces a controlled pre-tension force upon donning.

The IMU islands are seated beneath the overlapping sections of the dorsal backbone. The normal force generated by the pre-tensioned elastic components creates sufficient friction to mechanically lock the islands in place, minimizing relative sliding during vigorous dynamic movements.

4.2 | Flexible Interconnects and Sensor Integration

The distributed sensor array is interconnected via a set of custom multi-layer FPCs designed to withstand repeated bending cycles. The stack-up comprises two 35 μm copper foil layers encapsulated between three layers of 25 μm polyimide, bonded by two additional 25 μm adhesive interlayers. The geometric profile of each FPC stripe is parametrically optimized to match the outer contour length of the corresponding digit at maximum flexion (fist gesture), thereby preventing any constraint on hand movements.

Each IMU island integrates a 6-axis IMU (BHI360, Bosch Sensortec) featuring triaxial gyroscopes and accelerometers. To implement the stress-shielding “sandwich structure,” the FPC is mechanically reinforced by a steel support plate (bottom) and a protective steel shield (top). Manufacturing of the “sandwich structure” involves a two-stage process: the bottom support is hot-pressed onto the FPC substrate for structural rigidity, whereas the top shield is soldered post-assembly.

Prior to deployment, each sensor unit undergoes a calibration routine utilizing static measurements. This process compensates for deterministic error sources, including gyroscope bias drift, accelerometer zero-g offset, and cross-axis sensitivity matrices. The resulting calibration parameters are stored in the sensor hub's nonvolatile memory and uploaded to the IMUs during system initialization.

4.3 | Sensor Hub Electronics

The wrist-mounted sensor hub (Figure 1d) is architected around a highly-integrated wireless system-in-package (SiP) (ESP32-S3-PICO-1, Espressif Systems). It integrates dual-core 32-bit microprocessors, a 2.4 GHz Wi-Fi-capable radio, and a configurable I/O matrix. To interface the MCU I/O voltage (3.3 V) with the low-power sensor array (1.8 V), the custom PCB incorporates dedicated level-shifting logic. The system is powered by a compact lithium-ion polymer battery (Model 802,025, 400 mAh) and regulated by a high-efficiency power management integrated circuit (ETA6093), which yields an operating time of approximately 2 h.

Data transactions between the SiP and the IMUs are executed via high-speed serial peripheral interface (SPI) buses. To minimize wire count, sensors on the same finger stripe share common clock and data lines, with individual addressing managed via dedicated chip-select lines.

4.4 | Firmware Architecture for Synchronized Acquisition

Upon power-up, each IMU is configured to sample local orientation at a fixed 800 Hz, timed by its internal oscillator. To achieve a stable end-to-end latency, the firmware employs a deterministic superloop architecture that decouples time-critical signaling from data processing.

4.4.1 | Command Broadcast

To implement the global synchronization mechanism, we modified the MCU's hardware abstraction layer to operate the I/O matrix in broadcast mode. This allows a single internal signal to be routed simultaneously to multiple physical lines. This technique is applied to SPI clock lines, data output lines, and chip-select lines during the broadcast (Figure 2c), ensuring sub-frame synchronization of the timestamp latch command.

4.4.2 | Data Retrieval

Following the broadcast latch, the firmware initiates sequential data retrieval. To maximize throughput, the two independent hardware SPI controllers are utilized in parallel, allowing simultaneous polling of two sensor stripes.

4.4.3 | Core Affinity

To eliminate time jitter from RTOS scheduling in the SiP, the task-critical superloop for broadcasting and SPI transaction is pinned to one microprocessor core (Core 0), whereas the second core (Core 1) handles the Wi-Fi protocol stack and background housekeeping. This separation ensures that the 800 Hz acquisition cycle remains strictly periodic and uninterrupted by wireless transmission overhead.

4.5 | Host-Side Telemetry and Real-Time Reconstruction

The host computer functions as the centralized aggregation node for kinematic synthesis. To preserve signal integrity, raw orientation packets and hardware timestamps are streamed from the sensor hub using a hybrid network topology: although the hub transmits wirelessly via Wi-Fi, the host workstation is tethered to the router via an Ethernet cable. This configuration minimizes wireless contention and packet latency jitter. At the protocol level, sensor data is encapsulated into fixed-length payloads to ensure deterministic transmission latency and prevent fragmentation overhead. The end-to-end latency of T-800 is approximately 5–8 ms, including IMU internal processing at 800 Hz (~1.25 ms), firmware processing and SPI retrieval for all 18 sensors (~1.2 ms), and Wi-Fi transmission under the Ethernet-tethered configuration (~2–5 ms). The host-side temporal and spatial calibration consists only of fixed-size matrix operations and contributes negligibly to the total latency. Under normal laboratory operation, we did not observe significant packet loss or dropout. Under severe Wi-Fi congestion, packet arrival jitter may increase; however, synchronization is based on hardware timestamps rather than packet arrival time, so moderate transmission jitter does not directly corrupt inter-sensor alignment. Sustained packet loss cannot be recovered and instead appears as missing samples in the synchronized 800 Hz

grid, which can be detected by the timestamp monitoring in the host-side reconstruction pipeline.

Upon receiving, the binary stream is unpacked into IMU-specific floating-point quaternions and timestamp tuples. A temporal calibration engine utilizes the anchor points captured during the broadcast synchronization phase to map each sensor's local clock to the global master clock. This mapping enables two critical operations: (i) *resampling*, where asynchronous measurements are interpolated onto a uniform, time-aligned grid; and (ii) *drift monitoring*, which continuously tracks oscillator deviation to verify synchronization stability independent of the calibration algorithm.

Following temporal alignment, the data undergoes spatial transformation. The calibration matrices derived in Section 2.3 (R_{IW}^W and R_H^I) are applied to the raw readings, mapping local sensor frames to anatomical bone frames in world coordinates. This synchronized, physically registered kinematic stream constitutes the primary dataset, logged for offline analysis.

4.6 | Hand Gesture Visualization

To better visualize the IMU readings and the underlying hand gestures, we employ MANO [35], a statistical model for human hand reconstruction that captures both hand pose and shape. MANO parameterizes a posed hand mesh with a subject-specific shape parameter $\beta \in \mathbb{R}^D$, and a pose parameter $\phi \in \mathbb{R}^{N \times 3}$. Here, $N = 16$ denotes the number of kinematic joints, and the n^{th} row $\phi_n \in \mathbb{R}^3$ specifies the rotation of joint n in axis-angle form. Given (β, ϕ) , MANO reconstructs a posed hand mesh with linear blend skinning (LBS) [45], while additionally incorporating pose-dependent corrective deformations to alleviate common skinning artifacts in extreme hand poses.

Specifically, MANO obtains the posed hand mesh vertices $V \in \mathbb{R}^{M \times 3}$ by applying LBS to the canonical and subject-specific mesh vertices $T \in \mathbb{R}^{M \times 3}$ with joint locations $J \in \mathbb{R}^{N \times 3}$ and blend weights $\mathcal{W} \in \mathbb{R}^{M \times N}$, which can be formulated as

$$\begin{aligned} V &= \text{LBS}(T, J; \mathcal{W}), \\ J &= f(\beta; \bar{T}, \mathcal{J}, \mathcal{S}), \\ T &= g(\beta, \phi; \bar{T}, \mathcal{S}, \mathcal{P}). \end{aligned} \quad (11)$$

The joint locations $J \in \mathbb{R}^{N \times 3}$ are computed in the canonical pose by applying a joint regressor weights $\mathcal{J}$ to the subject-specific mesh vertices; this regressor is encapsulated by $f(\cdot)$ and is driven by the template mesh vertices $\bar{T}$ together with a learned shape bases $\mathcal{S}$ and the coefficients β . The canonical mesh vertices T are computed by $g(\cdot)$, which starts from the same template mesh vertices $\bar{T}$, adding the shape-dependent deformations induced by β through $\mathcal{S}$, and further adding pose-dependent corrective deformations parameterized by a learned pose-corrective bases $\mathcal{P}$ and the hand pose ϕ . Finally, $\text{LBS}(\cdot)$ uses the blend weights $\mathcal{W}$ and the kinematic transformations implied by ϕ and J to deform T into the posed mesh vertices V .

In our implementation, we use the publicly available MANO model with pre-trained parameters $(\bar{T}, \mathcal{J}, \mathcal{S}, \mathcal{P}, \mathcal{W})$ learned from

a large-scale hand mesh dataset [35]. We set the shape parameter to zero ($\beta = \mathbf{0}$) to obtain a subject-agnostic hand mesh, and drive the MANO pose using rotations derived from the IMU readings to visualize the resulting hand gestures. As illustrated in Figure 4, the posed MANO meshes faithfully reproduce the performed hand gestures and exhibit good visual agreement with the corresponding gestures in the captured images.

Author Contributions

Haoyang Luo: conceptualization, methodology, software, data curation, investigation, validation, formal analysis, supervision, visualization, project administration, writing – original draft. **Zihang Zhao:** conceptualization, methodology, software, data curation, investigation, validation, formal analysis, supervision, visualization, project administration, writing – original draft. **Leiyao Cui:** methodology, software, data curation, investigation, validation, formal analysis, visualization, writing – original draft. **Saiyao Zhang:** software, data curation, visualization. **Liu Yang:** methodology, investigation. **Zhi Han:** funding acquisition, resources. **Xiyuan Tang:** supervision, funding acquisition, project administration, resources, writing – review and editing. **Yixin Zhu:** supervision, funding acquisition, project administration, writing – review and editing, resources.

Acknowledgments

Our sincere thanks go to Miss Qing Gao (Peking University) and Mr. Haikang Diao (Peking University) for data collection, Prof. Wei Liang (Beijing Institute of Technology) and Prof. Bing Ning (Beijing Institute of Fashion Technology) for their help in glove manufacturing, Mr. Lei Yan (LeapZenith AI Research) for mechanical design support, and Ms. Hailu Yang (Peking University) for her assistance in procuring every piece of raw material necessary for this research.

Funding

This study was supported by Brain Science and Brain-like Intelligence Technology-National Science and Technology Major Project; 2025ZD0219400; National Natural Science Foundation of China; 62376009; Wuhan Major Scientific and Technological Special Program; 2025060902020304.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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