Multimodal Data Acquisition to Inform Clinical Rehabilitation

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MSc Thesis

MSc in Biomedical Informatics

Democritus University of Thrace & ATHENA Research Center

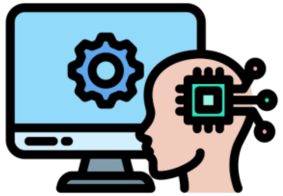
Saturday 28 March 2026

Artificial Intelligence and Motion Analysis

Healthcare & Rehabilitation

Sports Science

Activity Recognition Systems



Human - Computer Interaction

Artificial Intelligence in Rehabilitation

Technology and Artificial Intelligence used for:

- ✓ Improvement in results
- ✓ Promoting Active Participation
- ✓ Ensuring Compliance
- ✓ Personalization of therapeutic intervention


ELSEVIER
Artificial Intelligence in Medicine
Volume 146, December 2023, 102693

Research paper

Artificial intelligence in physical rehabilitation: A systematic review

Jennifer Sumner [b], Hui Wen Lim [b], Lin Siew Chong [b], Anjali Bundele [b], Amartya Mukhopadhyay [a b c], Geetha Kayambu [d]


SERMEF
Rehabilitación
Volume 59, Issue 2, April–June 2025, 100911

Review

Artificial Intelligence in rehabilitation: A narrative review on advancing patient care

Inteligencia artificial en rehabilitación: revisión narrativa sobre el avance del cuidado al paciente

A. Alshami [a], A. Nashwan [b c], A. AlDardour [d], A. Qusini [e]

The Supervision Gap: Solving Remote Patient Monitoring with AI-Driven Motion Analysis

Clinical Environment

- ✓ High accuracy but limited access
- ✓ High cost and "White Coat Effect"
- ✓ Adequate and Continuous supervision

VS

Home Environment

- ✓ High accessibility and comfort
- ✓ Absence of objective measurement
- ✓ Critical supervision gap

Limitations Affecting Real-World AI Rehabilitation Systems

Why do AI-based rehabilitation systems struggle transitioning from research environments to clinical practice?

- ✓ Unstable sensor synchronization
- ✓ Drift and anatomical misalignment
- ✓ Inconsistent exercise labeling
- ✓ Limited dataset availability

Reliable AI requires reliable, synchronized and anatomically consistent data.

Bridging Accuracy and Real-World Deployability

Optical Systems

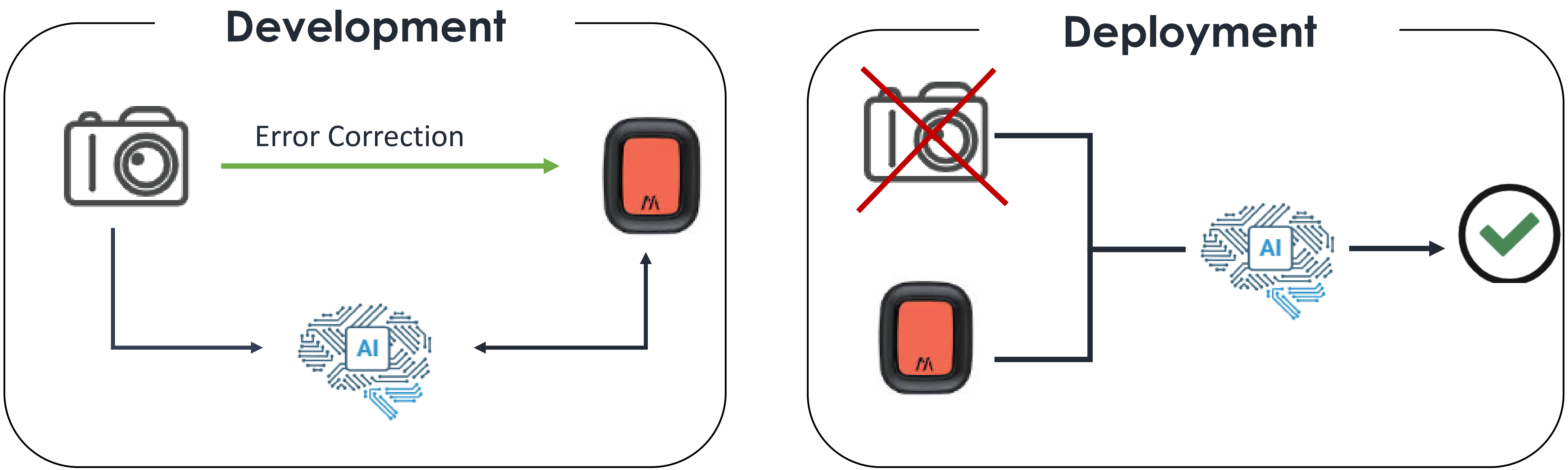
- ✓ High spatiotemporal precision
- ✗ Laboratory controlled environment
- ✗ Limited scalability for home use

Wearable sensors (IMUs)

- ✓ Real world deployable sensing
- ✓ Cost effective and portable
- ✗ Susceptive to drift and alignment errors

Multimodal synchronization bridges accuracy and scalability

From Multimodal Supervision to Sensor-Only Development



Multi-modal data collection is the bridge to reliable AI models for unsupervised recovery.

IMU Sensors - Technical Specification

Each IMU consists of:

- 3-axis Accelerometer
- 3-axis Gyroscope
- 3-axis Magnetometer

They can measure:

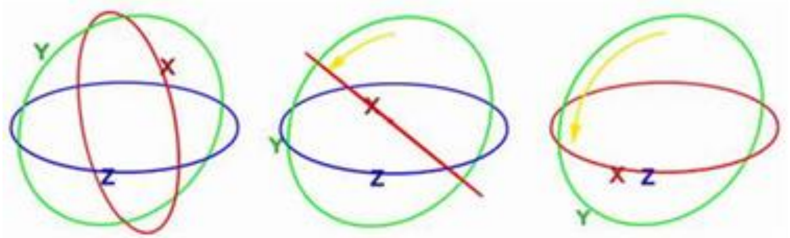
- Orientation
- Linear acceleration
- Angular Velocity
- Magnetic Field

By combining these data streams through sensor fusion algorithms like Kalman Filters, the system compensates for individual sensor weakness to provide a stable orientation estimate.

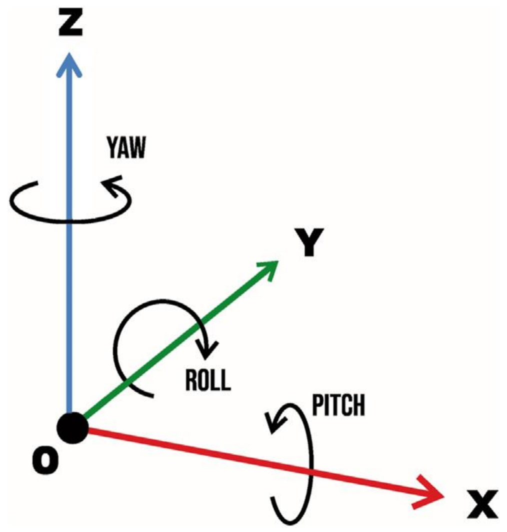
3D Orientation Representation for Motion Analysis

Euler Angles

- Defines rotation as a sequence of three angles
- Intuitive and easy to visualize
- Gimbal Lock: Loss of a degree of freedom



How Roll, Pitch and Yaw look like?

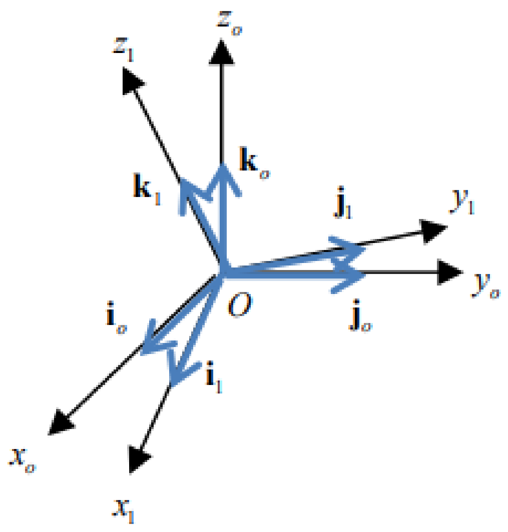


3D Orientation Representation for Motion Analysis

Rotation Matrix

- ✓ Mathematically robust
- ✓ Easy to chain rotations
- ✓ Computationally inefficient

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}$$



3D Orientation Representation for Motion Analysis

Quaternions

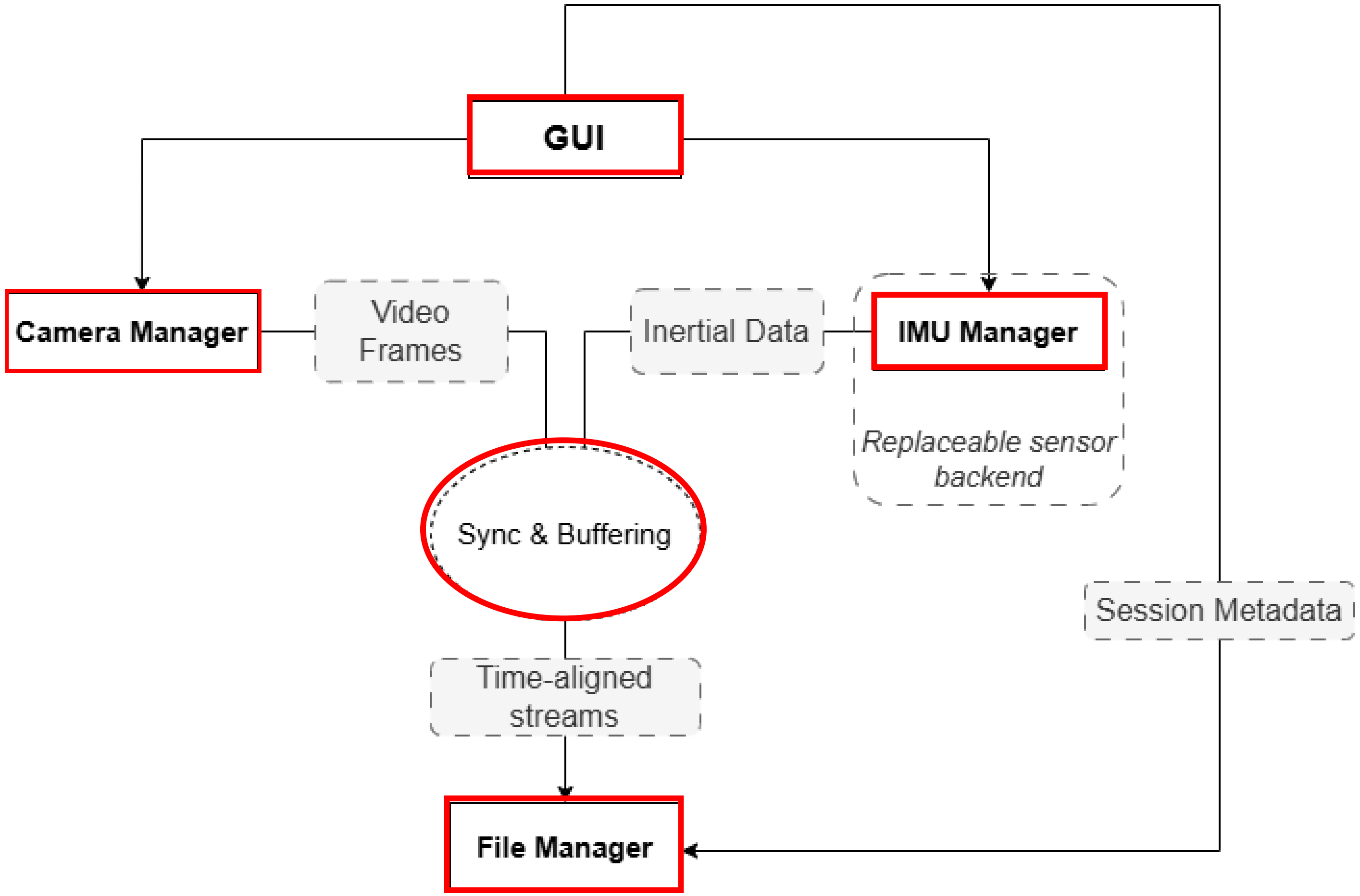
- ✓ 4-dimensional number representation
- ✓ Avoiding anomalies
- ✓ Computational efficiency
- ✓ Smooth interpolation
- ✓ No Gimbal Lock

Real Part

Imaginary Parts

$$q = w + xi + yj + zk$$

Recording Studio – System Architecture



- ✓ **Centralized Control Layer**
  GUI-based configuration and session management
- ✓ **Concurrent Multi-stream Acquisition**
  Event driven concurrent multi-stream acquisition
- ✓ **Time aligned Dataset generation**
  Buffered synchronization before storage
- ✓ **Replaceable Sensor Backend**
  IMU Manager can be adapted to different wearable devices

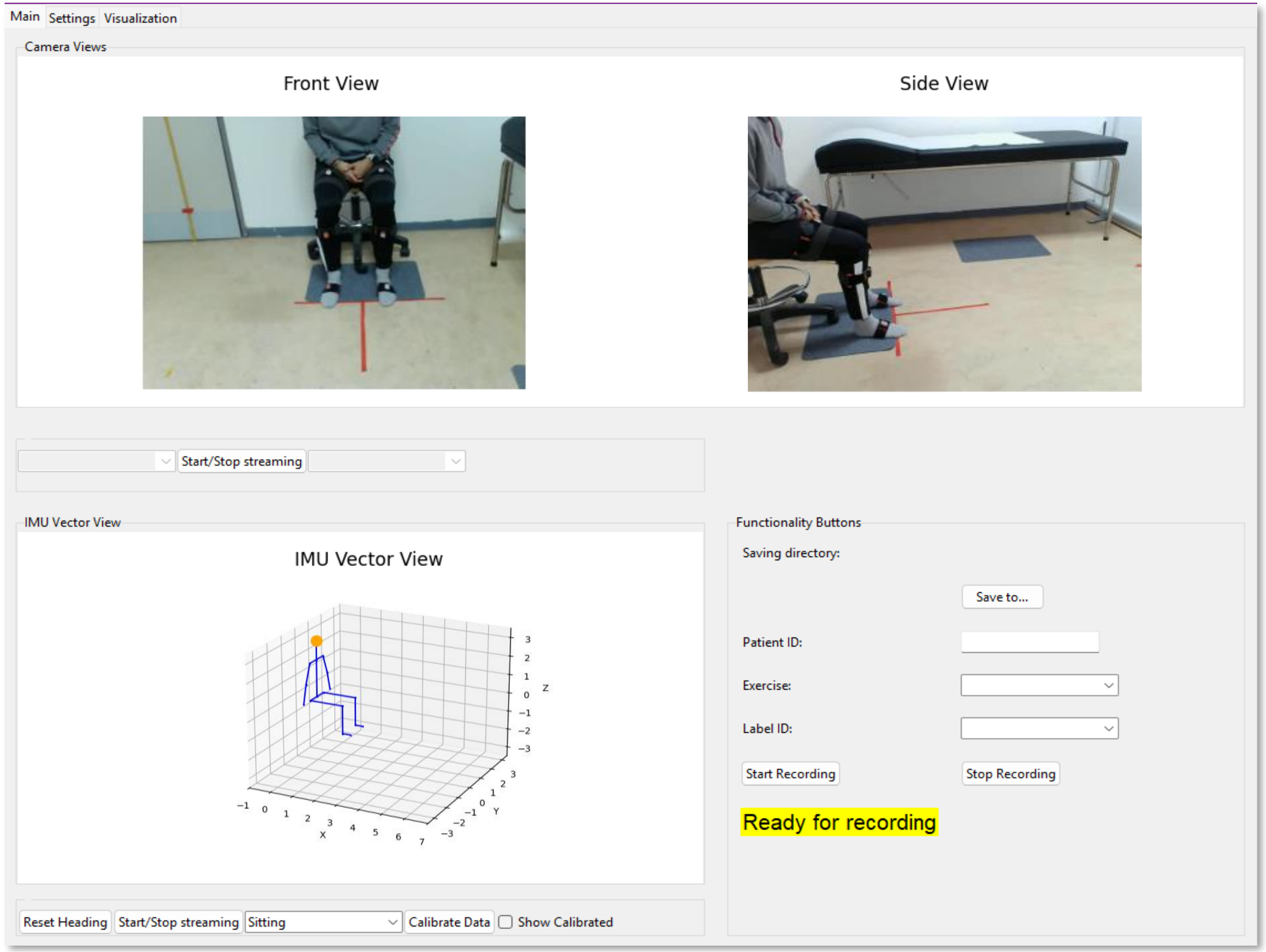
Multi-threaded Architecture for Sensor and Video Processing

Thread ID	Function	Used during
Thread 0	Camera 1 streaming	Recording/ Streaming
Thread 1	Camera 2 streaming	Recording/Streaming
Thread 2	IMU streaming (3D preview)	Streaming
Thread 3	IMU 3D pose plotting	Recording
Thread 4	Camera figure updates	Recording
Thread 5	Data collection	Recording

- The system uses 6 dedicated threads to separate processing for IMUs, cameras, GUI updates, and data saving.
- Each thread is assigned a specific task, ensuring smooth and responsive operation even under load.
- Thread control is handled using thread flag booleans and Python's "threading.Thread".

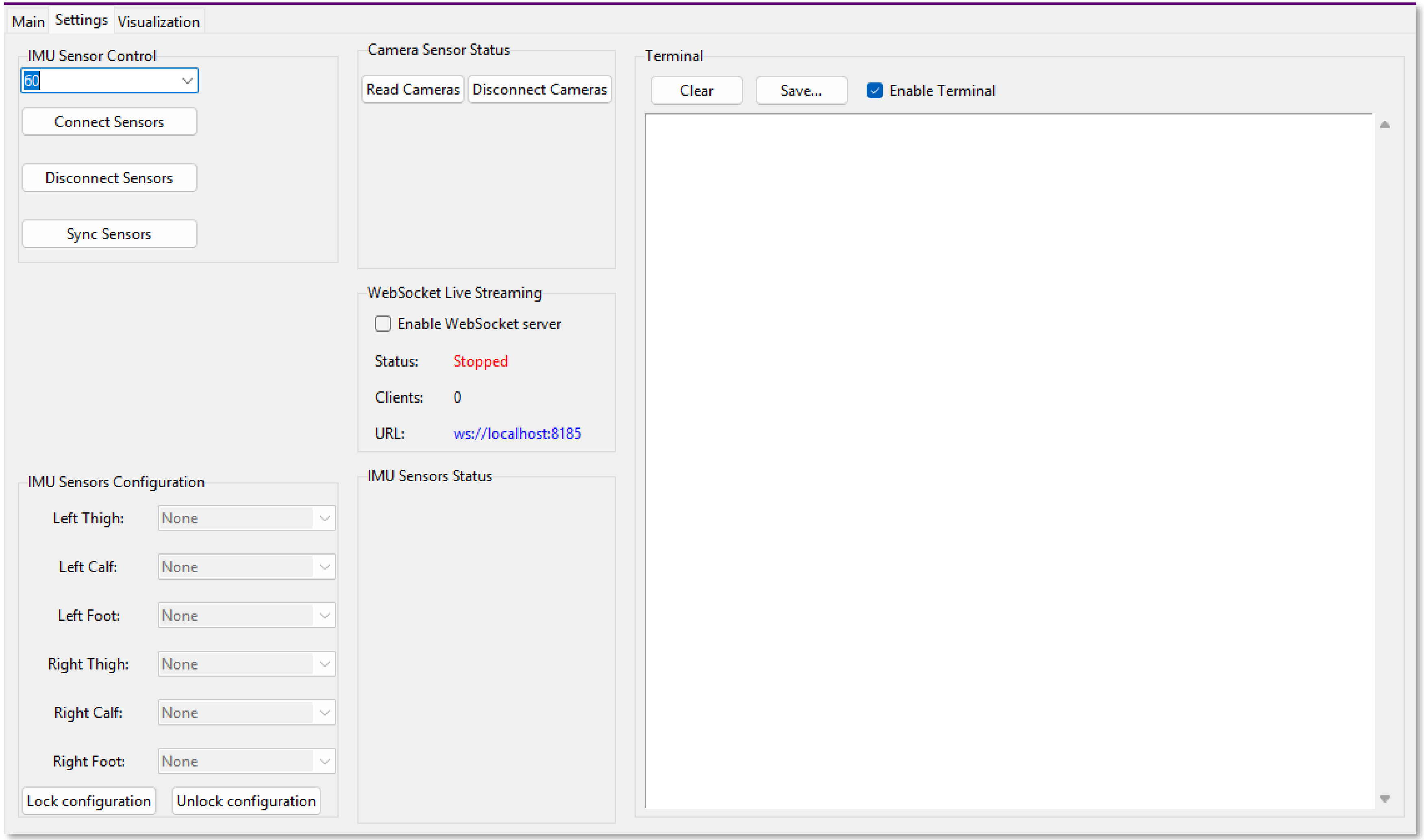
Integrated Control and Visualization Environment

Main Tab



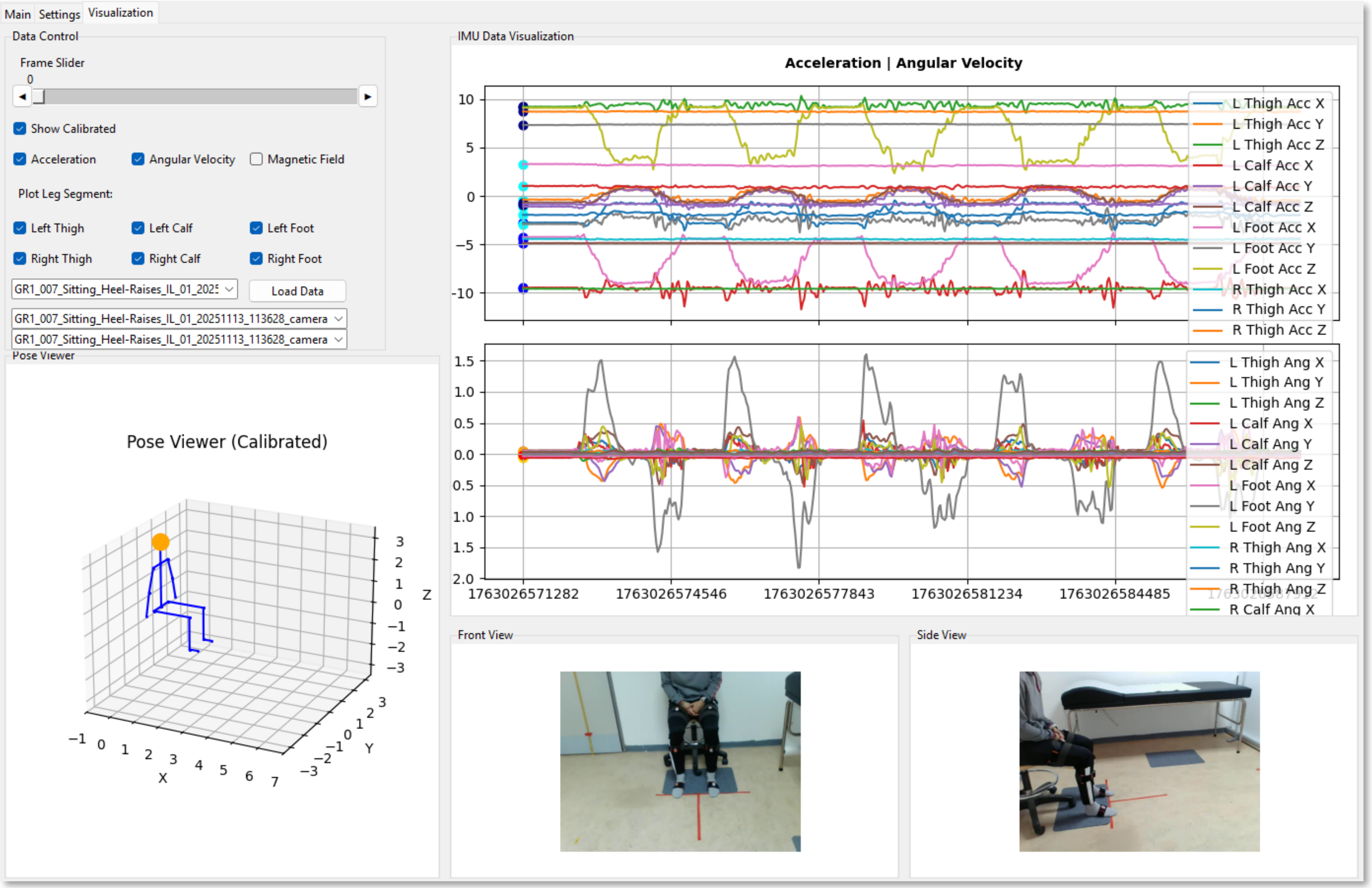
Integrated Control and Visualization Environment

Settings Tab

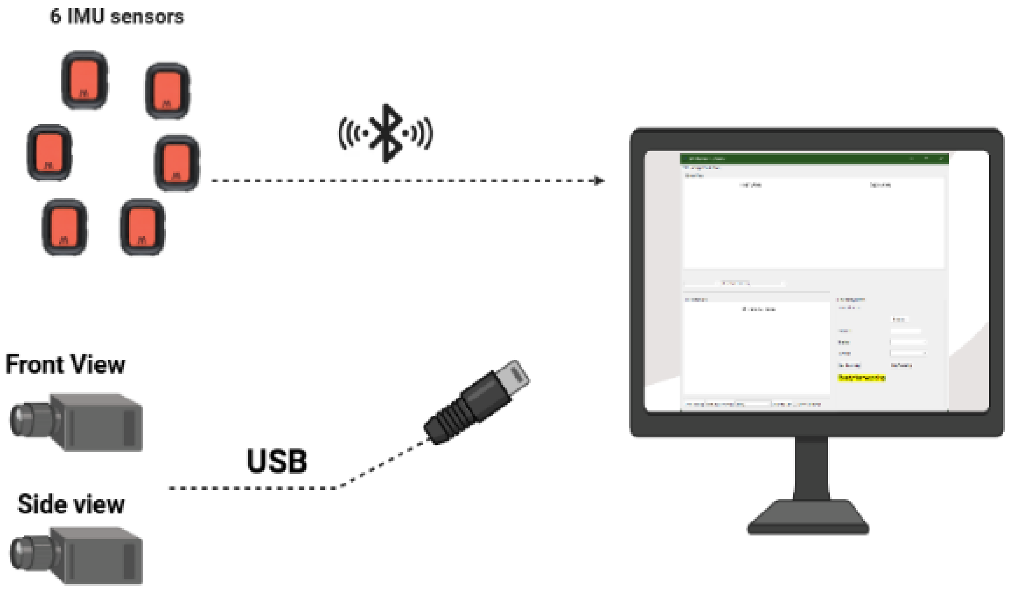


Integrated Control and Visualization Environment

Visualization Tab

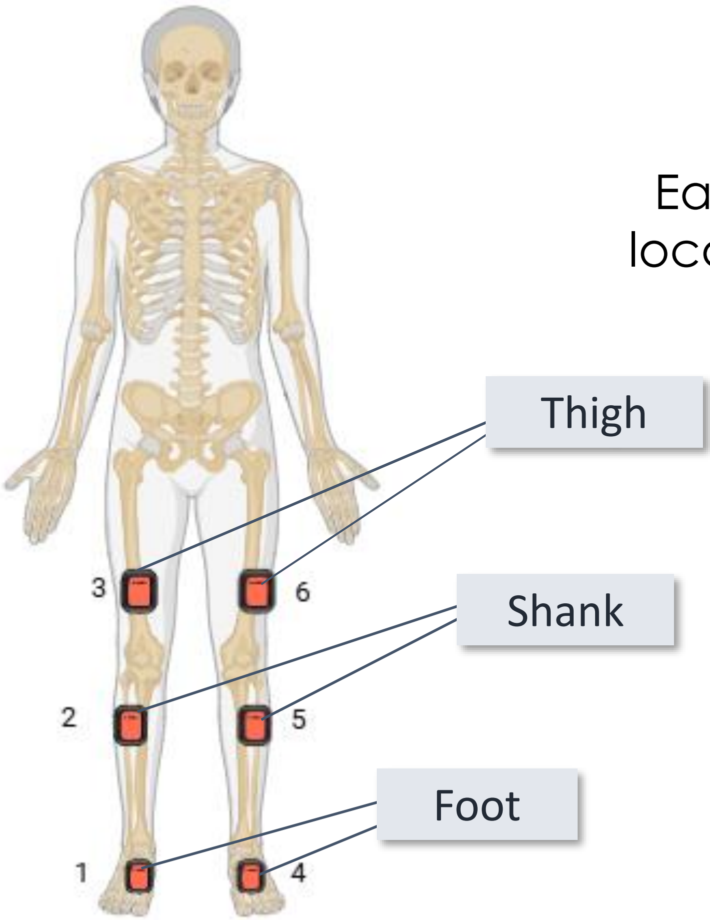


Recording Studio - Multimodal Recording and Data Export

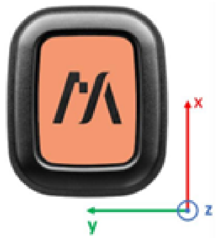


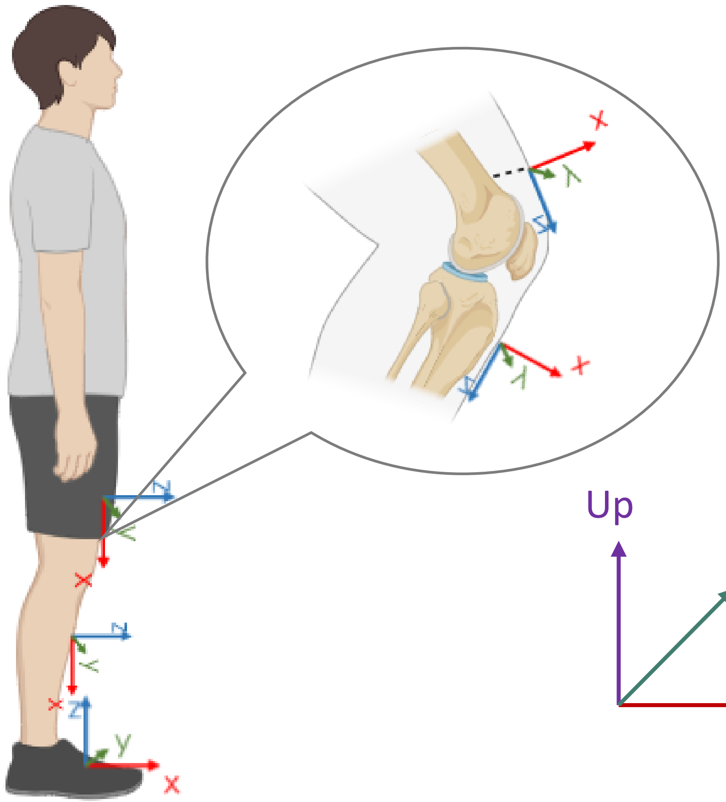
- Six Movella DOTs concurrent BLE streaming with synchronized inertial timestamps.
- Frontal and lateral optical recording for multimodal supervision.
- Frame - rate alignment:
  30 Hz inertial sampling & 30 fps video capture.
- Multithreaded Architecture for real-time streaming and synchronized data storage
- Implementation: Python using: Tkinter, threading, Matplotlib, Numpy, Pandas, OpenCV

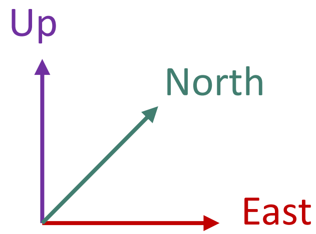
Sensor Placement and Coordinate System Mapping



Each IMU reports signals in its local coordinate system (X-Y-Z)

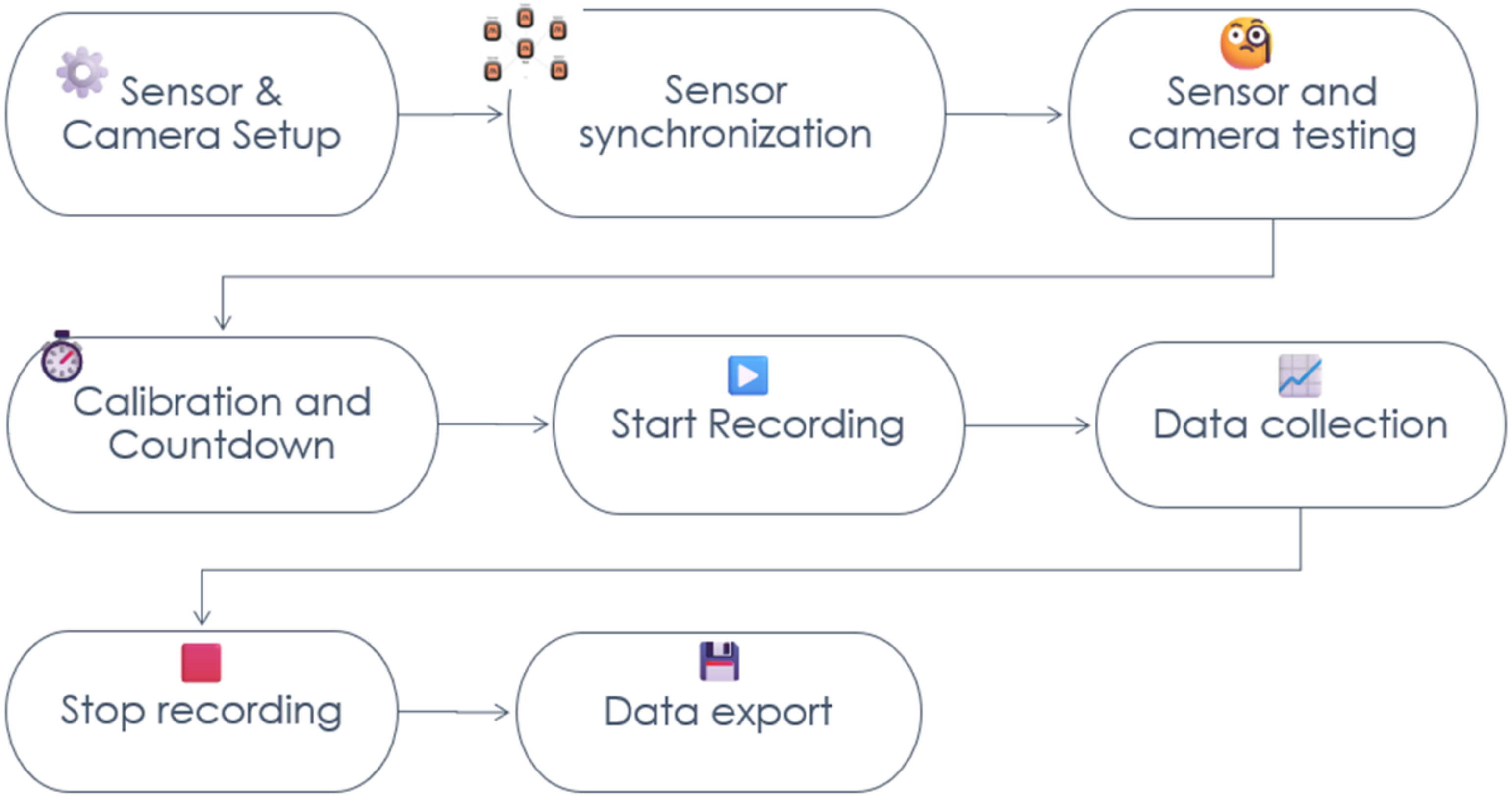






Reliable kinematic estimation requires consistent sensor-to-segment alignment across all local coordinate systems.

Data Collection Workflow



Structured Data Output for Post Processing

Save data include:

IMU:

- *.csv:
  - timestamp
  - quaternions,
  - acceleration,
  - angular velocity,
  - magnetic field
  - Pose (sitting or laying)
- *.txt *(XGM compatible format):*
  - timestamp
  - quaternions
  - acceleration
  - angular velocity

Camera :

- *_camera1.mp4
- *_camera2.mp4

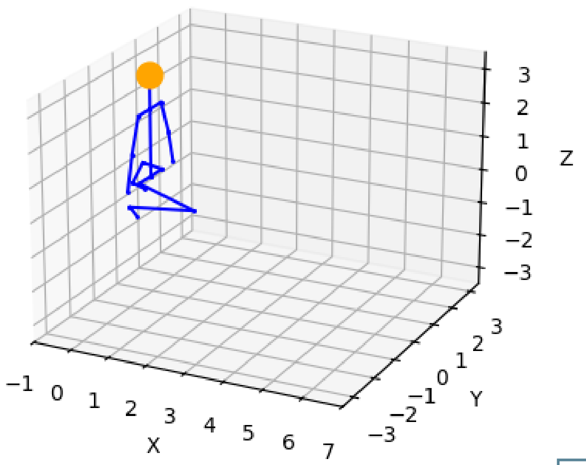
- IMU data is stored **based on the configuration mapping** locked prior to recording.
- All data is saved with unique filenames including patient ID, posture, exercise name, label ID, trial number and timestamp.

Example:
{patient_id}_{posture}_{exercise_name}_{label_ID}_{trial_number}_{timestamp}.{extension}

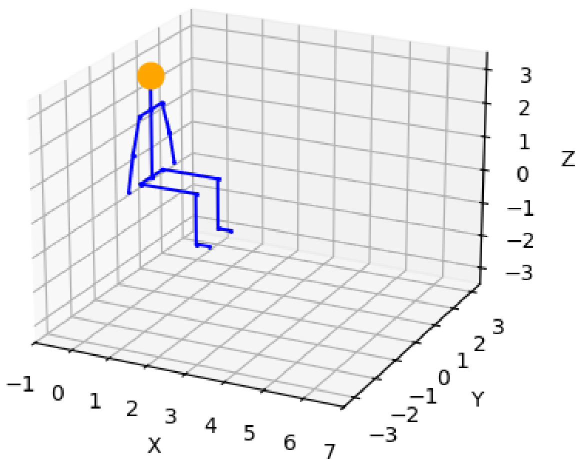
Static calibration for Anatomically Consistent 3D Pose

Local sensor frames are aligned to anatomical segment references through quaternion normalization.

Before (Uncalibrated)



After (Calibrated)



$$q' = q_{calib}^{-1} * q$$

Temporal Consistency Across Six IMUs

33.4 ± 0.5 ms

Mean sampling interval
N≈6,000

<0.004%

Packet Loss

29.9 ± 0.2 Hz

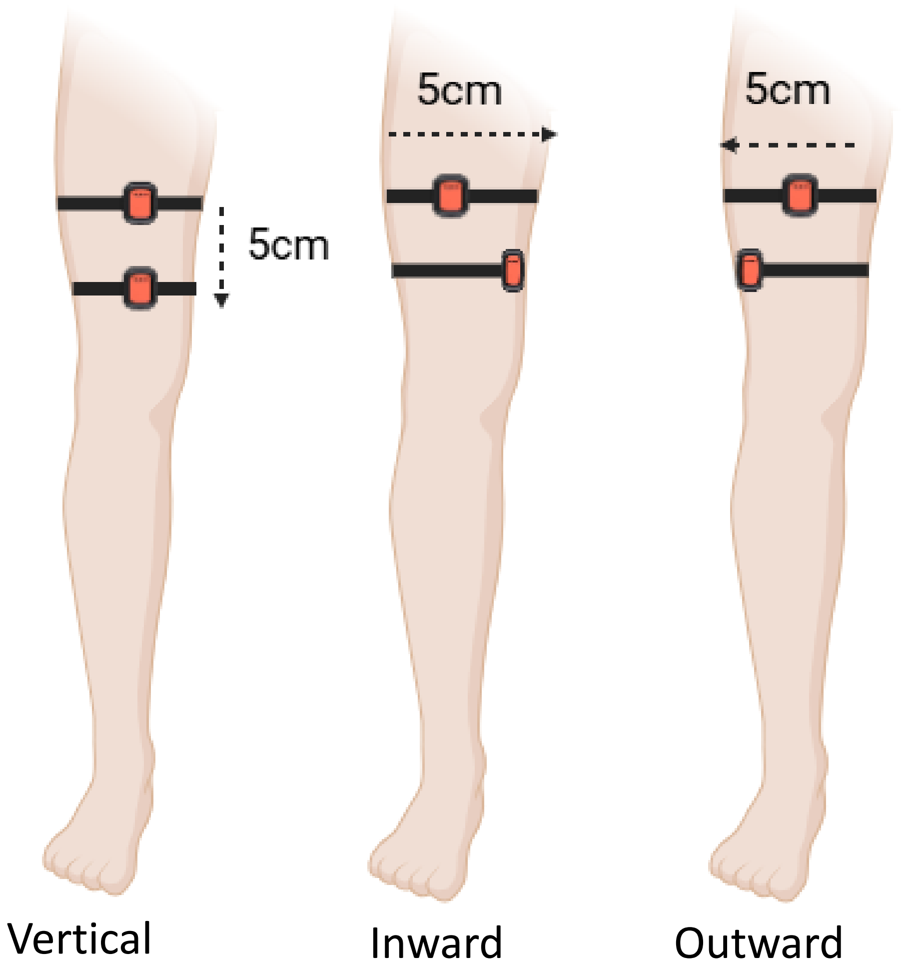
Experimental Frame Rate
(Target: 30Hz)

Δt

IMU_0_sensor_ts	IMU_1_sensor_ts	IMU_2_sensor_ts	IMU_3_sensor_ts	IMU_4_sensor_ts	IMU_5_sensor_ts
3447694	3447694	3448027	3447694	3447694	3447694
3448027	3448027	3448360	3448027	3448027	3448027
3448360	3448360	3448694	3448360	3448360	3448360
3448694	3448694	3449027	3448694	3448694	3448694
3449027	3449027	3449360	3449027	3449027	3449027
3449360	3449360	3449694	3449360	3449360	3449360
3449694	3449694	3450027	3449694	3449694	3449694
3450027	3450027	3450360	3450027	3450027	3450027
3450360	3450360	3450694	3450360	3450360	3450360
3450694	3450694	3451027	3450694	3450694	3450694
3451027	3451027	3451360	3451027	3451027	3451027
3451360	3451360	3451694	3451360	3451360	3451360
3451694	3451694	3452027	3451694	3451694	3451694
3452027	3452027	3452360	3452027	3452027	3452027
3452360	3452360	3452694	3452360	3452360	3452360
3452694	3452694	3453027	3452694	3452694	3452694

Stable concurrent BLE streaming under multimodal acquisition conditions.

Impact of Sensor Misplacement on Acceleration

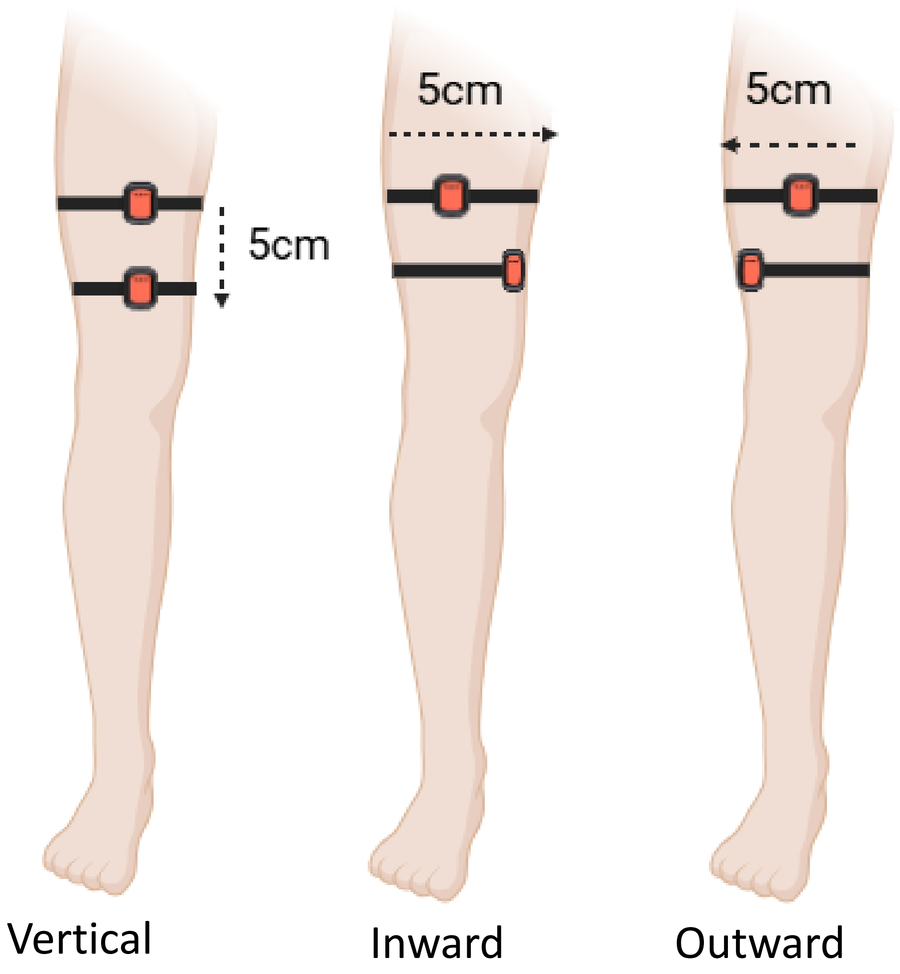


Vertical Misplacement (5cm) ↓
RMSE X: 0.045 ± 0.025 g *(static gravitational component)*
RMSE Y: 0.039 ± 0.020 g
RMSE Z: 0.10 ± 0.06 g
PAE Z: 0.2608 g

Inward Lateral Misplacement (5cm) ←
RMSE X: 0.104 ± 0.083 g
RMSE Y: 0.0055 ± 0.090 g
RMSE Z: 0.243 ± 0.307 g
PAE Z: 0.938 g

Outward Lateral Misplacement (5cm) →
RMSE X: 0.0735 ± 0.057 g
RMSE Y: 0.079 ± 0.148 g
RMSE Z: 0.131 ± 0.140 g
PAE Z: 0.505 g

Impact of Sensor Misplacement on Acceleration

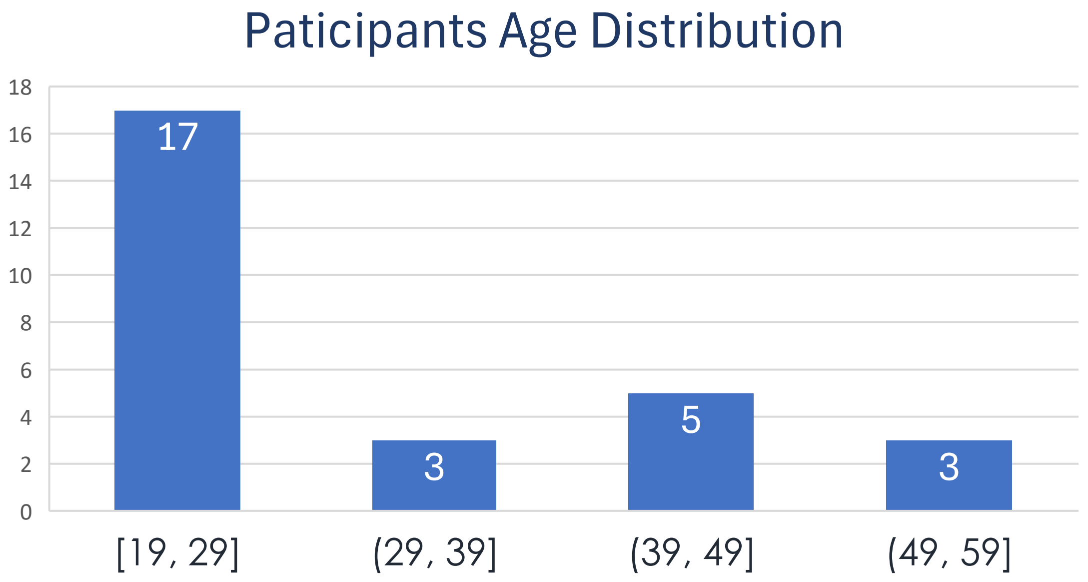


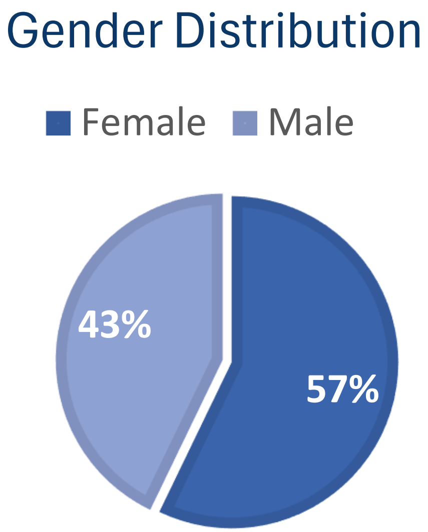
Results

This experiment demonstrates that lateral sensor displacement causes significantly higher acceleration errors compared to vertical shifts.

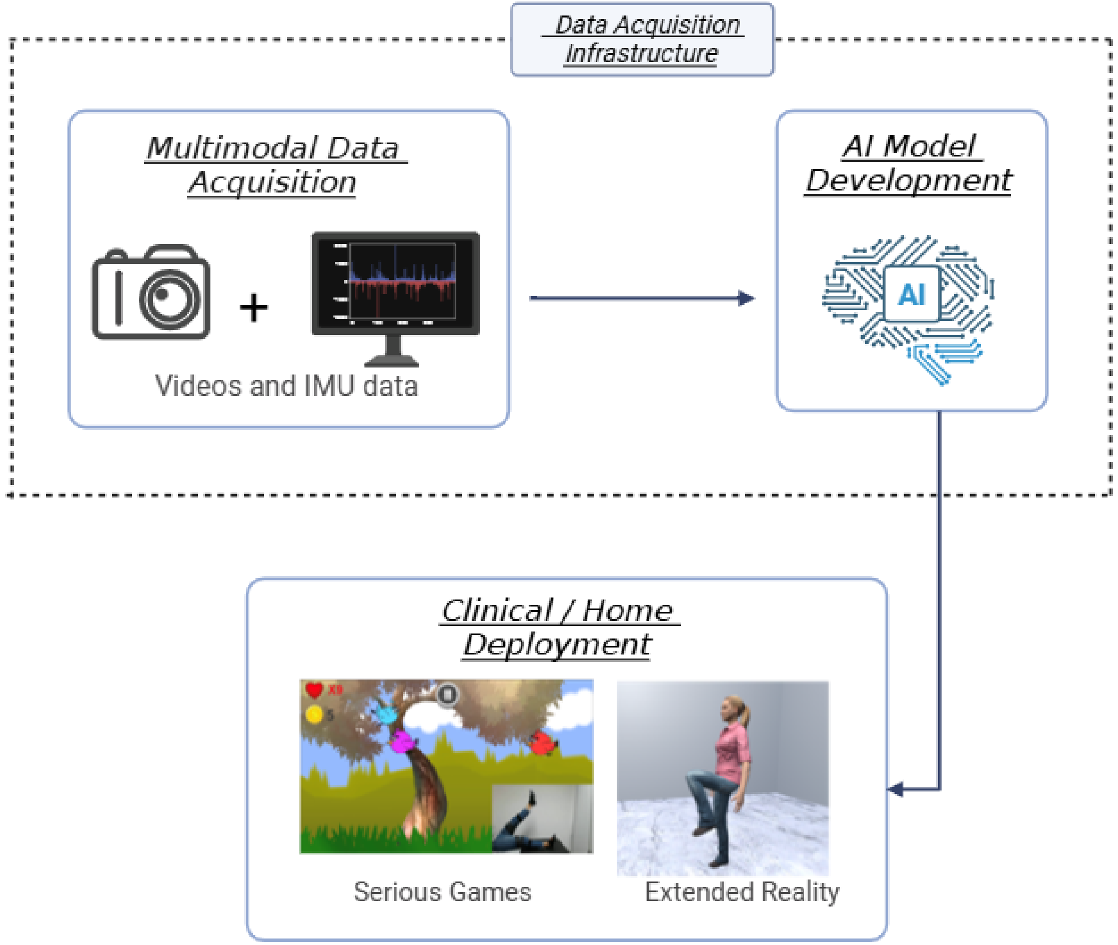
Data Collection Study

- ✓ Participants recorded so far: 28
- ✓ Participants performed a sequence of 59 exercise variations across the three designated postures (Standing, Sitting, Supine)
- ✓ Total recordings collected: ~6,900 files (from IMUs and cameras).





Towards an AI-Enabled Deployment



- ✓ Cross-modal synchronization validation
- ✓ Annotation & labeling
- ✓ AI model development for exercise classification

"The proposed infrastructure serves as the foundation for scalable, AI-enabled rehabilitation systems."

Thank you!

This Thesis was conducted in part within the context of European Union Horizon Europe project ThrombUS+, Grant Agreement No. 101137227.

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