

A Conceptualisation of Using a Portable Multi-Sensor Inertial System for Objective Mobility Assessment

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Abstract—This extended abstract presents pilot results from a portable, multi-sensor inertial measurement system, designed to objectively quantify movement across multiple standardized clinical mobility tests within a single unified framework. The system combines three wireless inertial measurement units (IMUs), placed bilaterally on the feet and at the trunk, streaming wirelessly to a microcomputer acting as a local access point and data logger. In an initial single-participant pilot spanning seven mobility tasks, the system achieved stable synchronized acquisition at 100 Hz with no detectable packet loss and produced inertial signatures sufficient to identify task-relevant movement events. These results establish proof of concept. A full feasibility evaluation will require testing on larger numbers of participants and repeated trials. As the system remains under active development, its hardware and software configuration may undergo further adjustments and refinements.

Index Terms—inertial measurement unit, wearable sensors, clinical mobility tests, gait analysis, feasibility

I. INTRODUCTION

Clinical mobility tests are standardized to evaluate fundamental movements required for independent daily functioning, and are routinely applied to assess *balance*, *lower-limb strength*, *functional endurance*, and *overall mobility* [1]. Among the most common tests are: chair-based transition tasks like sit-to-stand (STS), walking-based tests, for instance, the Timed Up and Go (TUG) test, and repetitive chair-rise protocols, including the five-times sit-to-stand (5xSTS) and one-minute sit-to-stand (1mSTS) tests [2]. These tests are quick to administer and require minimal equipment, but their outcomes are typically limited to total completion time or repetition counts obtained using a stopwatch and visual observation, which restricts the ability to capture movement quality, compensatory strategies, and subtle changes over time [2].

Inertial Measurement Units (IMUs) have increasingly been used to enhance such assessments by providing objective,

high-resolution measurements of movement patterns and temporal characteristics, with high reliability and validity for STS, balance, gait, and TUG outcomes [3]. However, many existing systems rely on a single-sensor configuration, laboratory-grade equipment, or test-specific implementation, which limit scalability and lack the flexibility to support multiple standardized tests within a unified framework [4]. This work reports the current state of a portable, multi-sensor system under ongoing development that addresses this gap, employing a three-IMU configuration placed bilaterally on the feet and at the trunk. As a first step, we evaluate the technical and practical feasibility of capturing and quantifying movement across a broad test battery in a single-participant pilot, rather than clinical interpretation or diagnostic performance.

II. MATERIALS AND METHODS

The system consists of three wearable IMUs positioned on the right and left feet and at the trunk at belt level, enabling simultaneous capture of bilateral lower-limb motion and trunk movement (see Fig. 1). Each unit integrated a Bosch BNO055 IMU with an ESP32-C3 microcontroller, powered by an 850 mAh lithium-polymer battery, at a fixed sampling rate of 100 Hz with the accelerometer range set to ± 16 g to prevent saturation during dynamic movements. Sensors were secured using single-use elastic fixation bands and custom 3D-printed housings.

Data and control commands are transmitted wirelessly to a microcontroller, with each sensor publishing to a dedicated topic to ensure traceability of data streams. The microcontroller hosted a local Wi-Fi access point, an MQTT broker, and a Python logging backend, storing time-stamped data in CSV and JSON formats. A web-based interface, accessed through a standard browser, allowed the operator to start and stop synchronized recordings and monitor sensor status, with

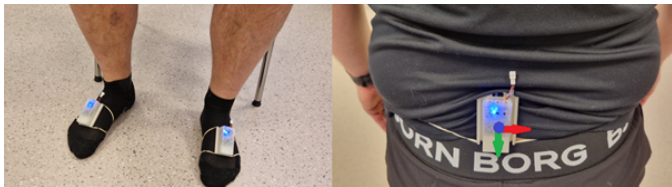


Fig. 1. Common placement of the sensors on the body for all tasks. The local sensor orientation indicated on the belt sensor: red, x axis; green, y axis; blue, z axis.

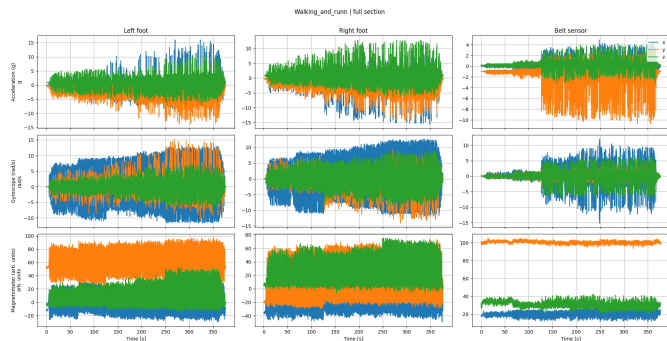


Fig. 2. Representative synchronized inertial signals recorded from the foot- and trunk-mounted sensors during one of the mobility tasks.

all components operating locally without external network infrastructure.

In this initial pilot, one healthy adult participant completed a standardized sequence of seven tasks: 5xSTS, 1mSTS, TUG, single-leg stance, deep squat, and treadmill walking at predefined speeds and inclines. The system was evaluated as a functional prototype intended to support stable data acquisition, and its mechanical design, sensor housing, and software configuration may be refined in subsequent development iterations. Recordings were initiated and terminated simultaneously across all sensors to ensure temporal alignment. Evaluation addressed technical feasibility (stable connectivity, synchronized start/stop, continuous streaming, and uncorrupted files), signal quality and event detectability (clear inertial signatures and preserved timing integrity for identifying task-relevant events), and practical feasibility (sensor placement effort and operator burden).

III. PRELIMINARY RESULTS

The results are based on a single-participant pilot and demonstrate system-level measurement capability rather than clinical findings. Each sensor recorded measurements at 10 ms intervals, corresponding to the target 100 Hz, with no detectable packet loss. Across all seven tasks, the system responded correctly to interface commands and successfully recorded all data files.

The recorded waveforms contained clear, interpretable signatures, enabling identification of task-relevant events, including sit-to-stand and stand-to-sit transitions for chair-based tests, gait- and turn-related phase changes for the TUG, descent and ascent phases for deep squats, postural sway during

single-leg stance, and gait-event timing across speed and incline transitions during treadmill protocols. A representative example of the synchronized multi-sensor signals recorded during one task is shown in Fig. 2. Stable inter-sample timing and preserved temporal alignment across sensors were interpreted as evidence of reliable acquisition. The unified three-sensor configuration was deployed without difficulty, with sensor readiness easily verified through onboard RGB LED feedback and the web interface, requiring no reconfiguration between tasks.

IV. DISCUSSION AND CONCLUSION

This single-participant pilot indicates that a portable, infrastructure-independent sensor configuration can support a broad battery of standardized mobility, balance, squat, and treadmill-based assessments within a unified framework. The system maintained synchronized 100 Hz acquisition without packet loss and produced inertial signatures sufficient for event detection across all evaluated tasks. These findings are preliminary: as a single-participant pilot, they establish proof of concept for the acquisition framework but do not yet constitute a feasibility evaluation. A robust assessment of feasibility will require testing on a larger number of participants and repeated recordings of each task per participant, allowing within- and between-subject variability in recording success, signal quality, and event detectability to be characterized. This is the focus of the planned extended study currently under development.

Building on this acquisition framework, subsequent work will develop algorithms for automated event detection, repetition counting, and spatiotemporal parameter extraction. Future iterations of the system may also incorporate concurrent physiological monitoring, such as heart rate, to complement kinematic measures with information on cardiovascular effort and recovery during mobility tasks. As these are preliminary results from a system still under active development, the hardware and software configuration may undergo further adjustments and changes before the extended study, and the findings should be interpreted accordingly. The presentation will demonstrate representative recordings from the evaluated tasks and discuss the next stages of system development.

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Proposed Wireless Motion Assessment System

Preferred technologies for functional mobility, balance, gait and sit-to-stand analysis

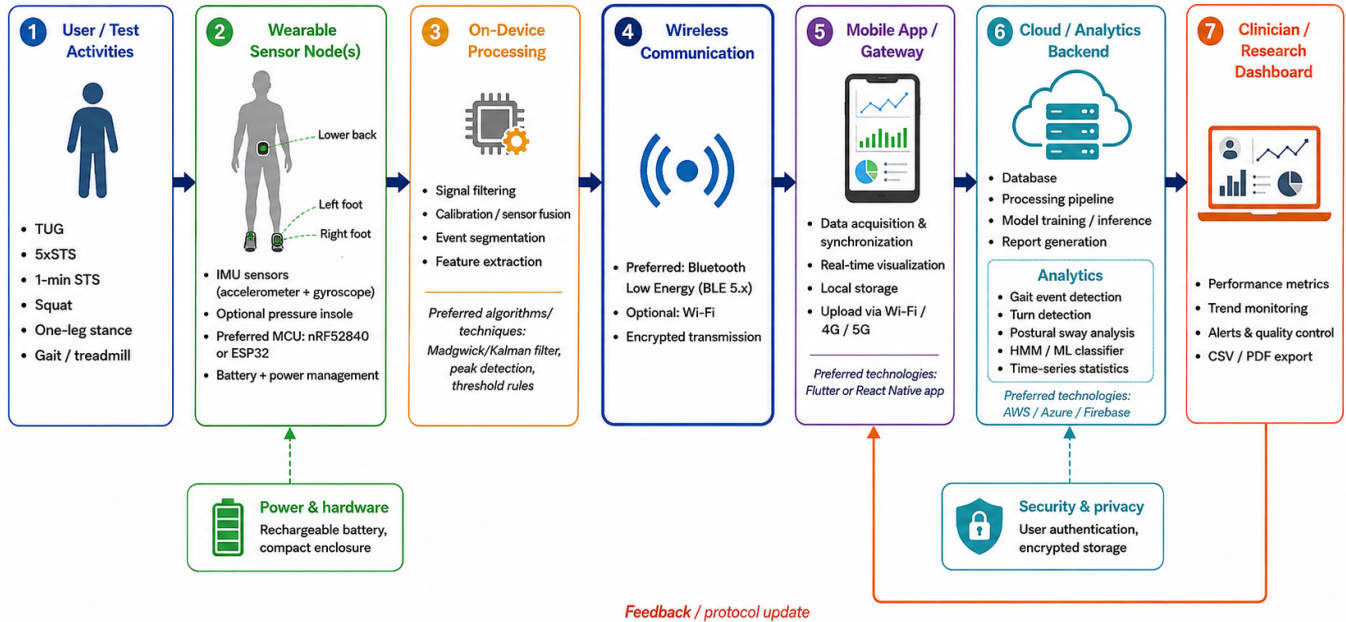


Fig. 3. A functional block diagram of the system.

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TABLE I
USER DRIVEN DESIGN

General Functionalities	Specific Functionalities	Constraints	Possible Technologies / Algorithms
Functional mobility assessment	Detect sit-to-stand and stand-to-sit transitions	Movements may be slow, asymmetric, incomplete, or supported by the arms. Chair height, armrests, and sensor placement can affect signal quality.	IMU-based posture detection, vertical acceleration analysis, gyroscope thresholding, peak detection, rule-based event segmentation, finite-state machines, supervised classification
Walking and turning assessment	Identify walking and turning phases during the Timed Up and Go test (TUG)	Turning may be irregular; walking speed varies between users; small spaces may limit movement patterns.	IMU gait segmentation, yaw-angle estimation, turn detection using gyroscope signals, Hidden Markov Models, Dynamic Time Warping, threshold-based phase detection
Repetition counting	Count repetitions in 5xSTS and one-minute sit-to-stand tests	Fatigue may change movement quality; partial or failed repetitions may be difficult to classify.	Repetition detection, acceleration peak counting, finite-state machines, signal envelope analysis, rule-based classifiers, machine-learning classifiers
Lower-limb strength / squat assessment	Measure timing of squat descent and ascent; estimate squat depth proxies	Squat depth is difficult to estimate without reference markers. Compensatory trunk movement may affect accuracy.	IMU orientation estimation, joint-angle proxy estimation, depth-camera skeleton tracking, temporal phase detection, regression models
Balance assessment	Detect postural sway characteristics and loss-of-balance events during one-leg stance	Small sway movements require high signal sensitivity. External support, foot repositioning, or sensor drift may distort results.	Center-of-mass proxy estimation, sway amplitude and frequency analysis, stabilogram diffusion analysis, accelerometer variance, anomaly detection
Gait-event and gait-parameter assessment	Detect heel strike, toe-off, step time, stride time, cadence, stance phase, and swing phase	Accuracy may change with walking speed, incline, footwear, sensor placement, or abnormal gait patterns.	Foot-mounted IMUs, pressure insoles, zero-velocity update, gait event detection, wavelet analysis, peak/valley detection, supervised machine-learning models
Treadmill condition analysis	Compare gait parameters across different speeds and inclines	Treadmill gait differs from overground walking. Incline modifies posture, propulsion, and foot contact patterns.	Time-series normalization, condition-based feature extraction, repeated-measures analysis, clustering, mixed-effects models
Signal quality and event detectability evaluation	Determine whether recorded signals allow clear identification of key movement events and phase boundaries	Signal noise, missing data, low sampling frequency, sensor drift, and inter-user variability can reduce reliability.	Signal filtering, sensor fusion, feature extraction, quality indexes, validation against video, force plate, or manual labels, accuracy/F1-score evaluation
Communication	Enable wireless data transmission between sensors, gateway, mobile app, and dashboard	Communication must be robust, reliable, suitable for multi-sensor streaming, and secure for clinical deployment. Data loss or disconnection should be minimized.	Implemented: local Wi-Fi/MQTT communication through a Raspberry Pi gateway for multi-sensor streaming. Future options: BLE for low-power data streams where data rates permit, encrypted communication, packet-loss detection, buffering, automatic reconnection, and device pairing/authentication
Clinical dashboard	Display performance metrics, trend monitoring, alerts, quality control, and report export	The dashboard must be secure, easy to interpret, and suitable for clinical review. Data should be exportable and traceable.	Implemented: local web-based user interface for session control, sensor monitoring, and CSV file management. Future options: role-based access control, secure local or cloud-based backend, interactive clinical dashboards, automated reporting, PDF export, alert thresholds, and data-quality flags
Wearability	Support easy sensor placement and comfortable use across different body types	The device must be easy to place, flexible for different users, stable during movement, and comfortable during repeated tests.	Wearable IMU modules, adjustable straps, ergonomic casing, placement guidance, color/position coding, sensor-orientation calibration, attachment-detection checks
Security and privacy	Protect user identity, clinical data, and recorded movement data	User authentication, encrypted storage, secure transmission, and access control are required for clinical deployment. Compliance with data-protection requirements should be considered.	Implemented: pseudonymized participant/session identifiers for sensor recordings and local data storage. Future options: user authentication, encrypted storage and transmission, TLS/HTTPS, role-based access control, audit logs, secure backup, formal key-management procedures, and GDPR-oriented data handling
User accessibility	Provide mobile app or gateway interface for real-time use and data upload	The system should be usable by clinicians or operators with minimal training. It should support offline/local storage and optional upload when network access is available.	Implemented: Raspberry Pi gateway interface, real-time sensor status monitoring, local storage, and browser-based session control. Future options: dedicated mobile application, guided test workflow, synchronization queue, user-friendly error notifications, and controlled data upload
Data management and interoperability	Store, organize, export, and integrate assessment data with external systems	Data must remain consistent, traceable, and compatible with clinical or research workflows.	Implemented: structured local CSV/JSON storage, metadata-based file naming, and export. Future options: structured database, metadata tagging, API integration, Health Level Seven/Fast Healthcare Interoperability Resources (HL7/FHIR) compatibility if clinical-system integration is required, automatic backup, and versioned records
Calibration and setup	Guide sensor initialization, placement verification, and baseline calibration before tests	Incorrect placement or poor calibration can reduce measurement accuracy. Setup should be fast and repeatable.	Sensor calibration routines, orientation reset, baseline standing detection, placement validation, signal-quality check, guided setup workflow