Markerless 3D Analysis of Lower Extremity Movements

Mimicking Hemiplegia Using the Fugl-Meyer Assessment Paradigm

Toward a Virtual Coaching System

STRATIF-AI *project* · Part II of II

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The Congress of Physical and Rehabilitation Medicine & Balneology, Covasna, Romania · Covasna, 23 – 25 April 2026

Quick Recap — Part I Foundation

Everything we built — now applied to lower extremity

3×

GoPro Hero 12

1080p · 60 fps · hardware-sync · ~1.8 m

34

Landmarks / frame

MediaPipe Holistic · conf ≥ 0.5 · pose + hands

Stereo

3D Triangulation

Essential Matrix · stereo pair · rolling mean smoothing

5×

Severity levels

Normal · Mild · Moderate · Marked · Severe

Upper Extermity (UE) result: 15 movements · 811k rows → Same pipeline now applied to lower extremity

Lower Extremity Clinical Context — Why It Matters

Stroke impact on lower extremity · recovery pattern · functional consequences

Clinical Background

Faster — but incomplete

LL motor recovery is faster and more complete than UE, yet ~30% of survivors retain persistent gait deficit at 6 months*

Extensor synergy dominates

LL flexor synergy: hip/knee flexion + ankle dorsiflexion. Extensor synergy: hip/knee extension + plantarflexion — opposite to UE pattern**

Functional impact

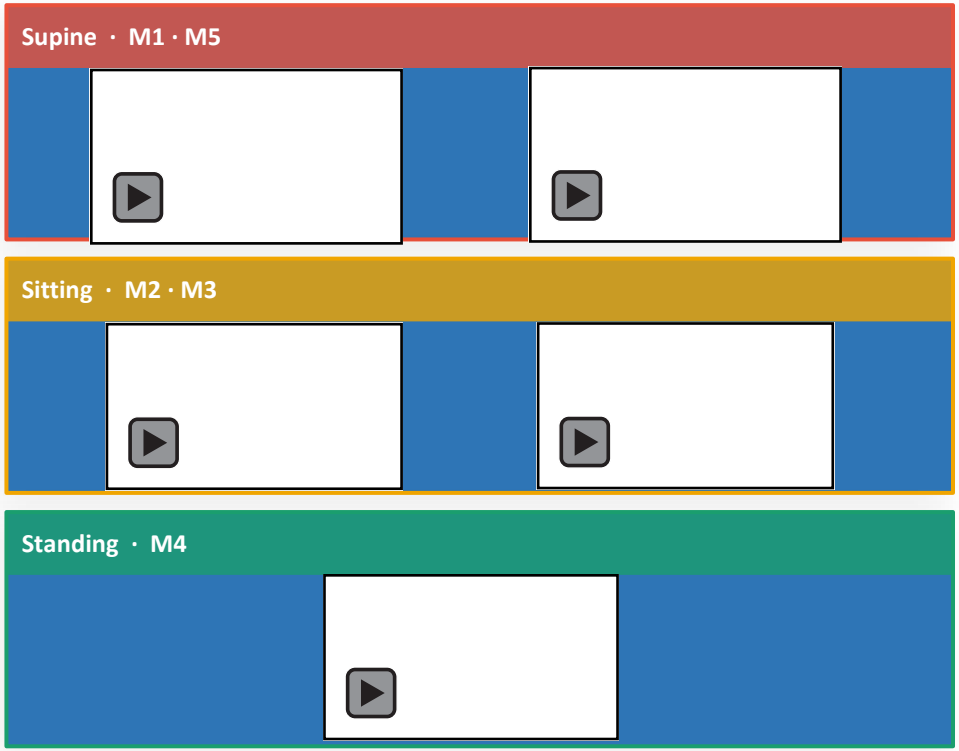
LL deficit = loss of independent mobility, fall risk, reduced community participation — directly affects QoL more than UE in many patients ***

3 distinct body positions

FMA-LE requires supine, sitting and standing — each position changes the biomechanical challenge and the camera occlusion pattern

Research gap

LE markerless 3D analysis remains less developed than UE — no standardized protocol exists for post-stroke rehabilitation assessment



*Jørgensen HS, et al. Arch Phys Med Rehabil. 1995;76(5):406-412
**Brunnstrom S. J Am Phys Ther Assoc. 1966;46(4):357-375
***Langhorne P, et al. Lancet Neurol. 2009;8(8):741-754

Lower Extremity Recovery — Brunnstrom Stages & FMA Mapping

How neurological recovery translates into measurable movement stages

~85%
walk independently by 6 months *

~30%
persistent LE deficit at 6 months *

FMA-LE
34 pts max
17 items**

Stage 1→6
Brunnstrom recovery map***

St.	Twitchell & Brunnstrom Stage — Clinical Description**	FMA-LE Movement***
1	Flaccidity — no voluntary movement	Reflex activity only
2	Spasticity begins — reflexive synergy responses	Minimal voluntary LE activity
3	Synergy peaks — M1: hip/knee/ankle within synergy	M1 — volitional movement within synergy
4	Voluntary separation begins — M2, M3	M2 knee flexion · M3 ankle dorsiflexion
5	Selective control — M4: hip flexion standing	M4 — hip flexion against gravity
6	Near-normal — M5: coordination and speed	M5 — heel-to-knee · tremor · speed

*Jørgensen HS, et al. Arch Phys Med Rehabil. 1995;76(5):406-412
**Fugl-Meyer AR, et al. Scand J Rehabil Med. 1975;7(1):13-31 Jørgensen HS, et al. 1995
***Brunnstrom S. J Am Phys Ther Assoc. 1966;46(4):357-375

Berg Balance Scale — Fall Risk Assessment in Post-Stroke LE

Complementary to FMA-LE · functional balance · fall risk stratification

Berg Balance Scale

What it measures

Functional balance and risk of falling — ability to maintain position and transition safely between postures

Items

14 tasks · 0–4 points each · max 56 points

Tasks include

Sitting unsupported · standing unsupported · transfers · standing eyes closed · tandem stance · single-leg stance · turning 360°

Time

~20 minutes · no special equipment required

Psychometrics

ICC 0.98 · sensitivity 91% · specificity 82% for fall prediction in stroke

Fall risk cutoffs

41–56	**Low risk** — Independent ambulator
21–40	**Medium risk** — Assistive device likely needed
0–20	**High risk** — Non-ambulatory wheelchair

Key threshold

< 45 pts → increased fall risk
< 36 pts → high fall risk
(~100% fall rate reported)

Why use both?

FMA-LE alone is not enough

FMA scores the neurological deficit — not whether the patient can stand safely or is at risk of falling.

Berg adds the functional dimension

A patient with mild FMA-LE deficit can still have poor balance and high fall risk. Berg captures what FMA misses.

Post-stroke fall rate is high

~40–70% of stroke survivors fall within the first year. LE motor deficit is a major predictor — but Berg quantifies the actual risk level.

Combined profile guides decisions

Low FMA + Low Berg = most vulnerable. Guides assistive device prescription, discharge destination, and rehab intensity.

Berg KO, et al. Physiother Can. 1989;41(6):304-311
Bogle Thorbahn LD, Newton RA. Phys Ther. 1996;76(6):576-583
Langhorne P, et al. Lancet Neurol. 2009;8(8):741-754
Jørgensen HS, et al. Arch Phys Med Rehabil. 1995

”Berg Balance Scale#*

B, A







Name: _____ Date: _____

Location: _____ Rater: _____

ITEM DESCRIPTION	SCORE (0-4)
Sitting to standing	_____
Standing unsupported	_____
Sitting unsupported	_____
Standing to sitting	_____
Transfers	_____
Standing with eyes closed	_____
Standing with feet together	_____
Reaching forward with outstretched arm	_____
Retrieving object from floor	_____
Turning to look behind	_____
Turning 360 degrees	_____
Placing alternate foot on stool	_____
Standing with one foot in front	_____
Standing on one foot	_____

Score of **< 45** indicates a **greater** **risk of falling**

45-56 = **low** **fall risk**; **21-40** = **medium** **fall risk**; **0–20** = **high** **fall risk**

Total _____ (**Maximum = 56**)’: **14** **items** x **4** **points**” (o. n.)

* https://www.brandeis.edu/roybal/docs/Berg-Balance-Scale_Website.pdf

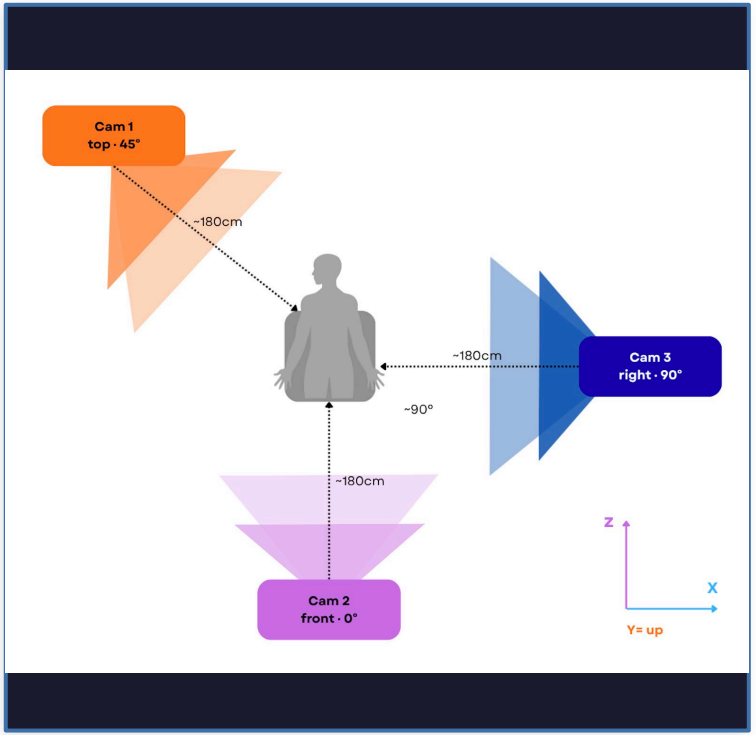
Recording Setup — Lower Extremity

Adapted camera positions for supine, sitting and standing positions

Camera	UL Session (Part I)	LL Session (Part II)
Cam 1	Top · 45° overhead	Top · 45° overhead
Cam 2	Right · lateral 90°	**Front · 0° frontal**
Cam 3	Front · 0° frontal	**Right · lateral 90°**

Cam 2 and Cam 3 positions differ from Part I — recorded in a separate session.
*Any camera repositioning requires full checkerboard recalibration**

M1 (supine)	Top + lateral cameras critical for knee/ankle angles
M2–M3 (sitting)	Frontal camera captures knee/ankle angle
M4 (standing)	All 3 cameras capture full-body posture
M5 (supine)	Frontal + top capture heel-to-knee trajectory



*Zhang Z. IEEE Trans Pattern Anal Mach Intell. 2000;22(11):1330-1334

Technical Challenges — Lower Extremity Recording

Occlusion · calibration · landmark selection · position-dependent camera strategy

Occlusion risk

Subject supine or sitting — lower body partially hidden from lateral cameras. Occlusion frequency increases with severity (less movement = less limb exposure).

Position-dependent angles

Each body position (supine / sitting / standing) requires different camera coverage priorities. No single angle is optimal for all 5 movements.

Separate session → recalibration

Any camera repositioning requires full checkerboard recalibration before data collection — Zhang method*, **Root Mean Square (RMD) < 1.9 px target.****

Lower complexity vs UE

Fewer fine motor landmarks, broader joint angles — technically simpler than hand tracking. But bilateral symmetry adds comparison opportunities.

Occlusion risk per position

Supine — HIGH



Lateral camera view of knee/ankle blocked by opposite leg or mattress. Top camera critical.

Sitting — MEDIUM



Hip/pelvis partially hidden. Frontal view preferred for knee angle.

Standing — LOW



Full body exposure from all angles. Best conditions for 3D reconstruction.

*Zhang Z. IEEE Trans Pattern Anal Mach Intell. 2000;22(11):1330-1334
**Hartley R, Zisserman A. Multiple View Geometry. Cambridge UP; 2003

Adaptations vs Upper Extremity — Landmarks & Occlusion

What changed technically when moving from UL to LL recording

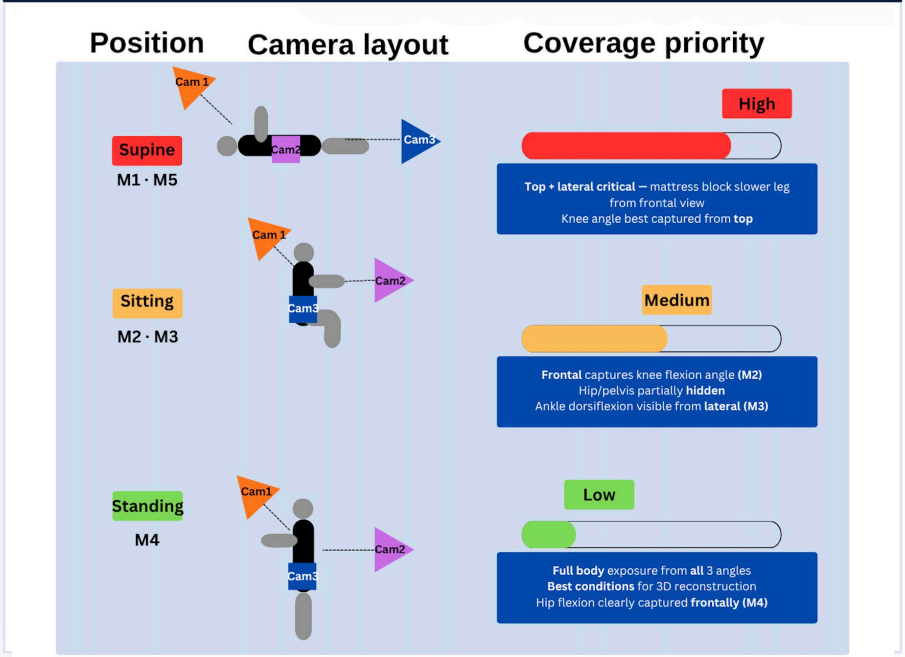
Landmark protocol

Shared (34 landmarks)	Shoulders, elbows, wrists, hips, all hand landmarks — identical to UL session
Added for LL (+2)	knee_left (idx 25) · knee_right (idx 26) — primary joints for LE kinematic analysis
Not needed for LL	Nose (idx 0) captured but not used — LL coordination test is heel-to-knee, not heel-to-nose

Complexity comparison — UL vs LL

	UL	LL
Fine motor landmarks	UL: 21 pts/hand + wrist	LL: knee + ankle only
Joint DOF tracked	UL: shoulder, elbow, wrist, 5 fingers	LL: hip, knee, ankle
Movement complexity	UL: high — grasp, pinch, coordination	LL: lower — gross joint patterns
Occlusion risk	UL: moderate (hand occasionally hidden)	LL: high — body blocks limb in supine/sitting

Camera strategy per body position



*Lugaresi C, et al. arXiv:1906.08172 (2019)
*Zhang Z. IEEE Trans PAMI. 2000;22(11):1330-1334
*Needham L, et al. J Biomech. 2022;138:111112

Technical Implementation

From Raw Video to 3D Kinematics

A six-step automated pipeline — open source, marker-free, clinically deployable

3×	34+	60	6
cameras	landmarks	fps	pipeline steps

01 Environment › 02 Intrinsic calib › 03 Extrinsic est. › 04 2D keypoints › 05 Stereo triangul. › 06 Smooth & export

What this section covers

01 Software environment and dependencies

02 Camera calibration — intrinsic and extrinsic parameters

03 2D landmark extraction with MediaPipe Holistic

04 3D reconstruction via stereo triangulation (cv2.triangulatePoints)

05 Rolling mean smoothing of kinematic trajectories (window=5)

06 Dataset structure and export format

Python · OpenCV · MediaPipe · NumPy · SciPy · Pandas — fully open source, no proprietary hardware required

Step 1 — Environment & Software Stack

Step 1/6

Python ecosystem · open-source · reproducible · no proprietary dependencies

Python 3.10 *Core language*	Stable LTS, broad ecosystem, reproducibility across platforms
OpenCV 4.x *Image processing & calibration*	Camera matrix computation, image undistortion, video I/O — de facto standard in computer vision
MediaPipe Holistic *Pose + hand landmark detection*	Single-pass detection of 33 pose + 21pts/hand landmarks from standard RGB video — no depth sensor required
SciPy / NumPy *Numerical computation*	Essential Matrix, stereo triangulation, linear algebra operations on landmark coordinates
Pandas *Data management*	Structured storage of per-frame landmark coordinates — enables fast filtering, grouping, and CSV export

requirements.txt

```
opencv-python>=4.8
mediapipe>=0.10
numpy>=1.24
scipy>=1.11
pandas>=2.0


# config
python==3.10
conf_threshold=0.5
window_rm=5
# rolling mean, window=5
```

Env › Intrinsic › Extrinsic › Keypoints › DLT › Export

*Bradski G. The OpenCV library. Dr. Dobb's Journal. 2000;25(11):120-125
*Lugaresi C, et al. arXiv:1906.08172 (2019)
* Virtanen P, et al. Nat Methods. 2020;17:261-272

Step 2 — Intrinsic Camera Calibration

Zhang method · checkerboard pattern · per-camera · RMS < 1.9 px

Step 2/6

RMS < 1.9 px

What is intrinsic calibration?

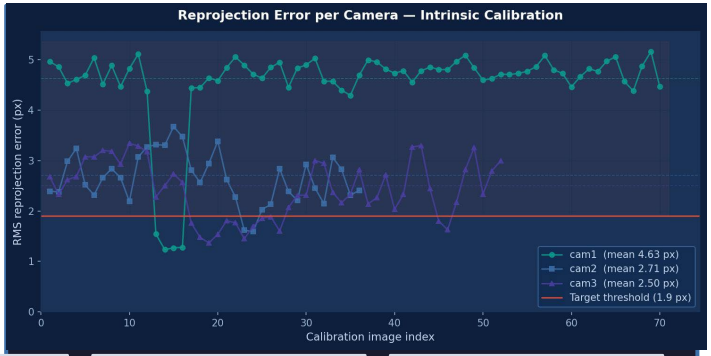
Intrinsic parameters describe the internal optics of a camera — focal length (fx, fy), principal point (cx, cy), and lens distortion coefficients (k1, k2, p1, p2). Without calibration, straight lines appear curved in the image and 3D reconstruction accumulates systematic errors.



Camera matrix K

$$K = \begin{bmatrix} fx & 0 & cx \\ 0 & fy & cy \\ 0 & 0 & 1 \end{bmatrix}$$

fx, fy	Focal length in pixels — determines zoom/magnification
cx, cy	Principal point — optical center of image
k1, k2	Radial distortion — barrel/pincushion lens effect



Procedure

Checkerboard 8×6 inner corners · filmed from 20+ angles per camera · OpenCV findChessboardCorners() + calibrateCamera() · per-camera matrix stored · RMS reprojection error

Env › **Intrinsic** › Extrinsic › Keypoints › DLT › Export

*Zhang Z. A flexible new technique for camera calibration. IEEE Trans Pattern Anal Mach Intell. 2000;22(11):1330-1334
*Bradski G. Dr. Dobb's Journal. 2000;25(11):120-125

Step 3 — Extrinsic Camera Estimation

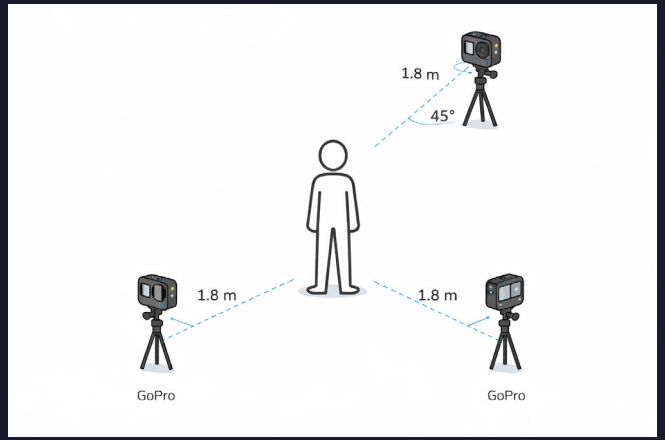
Per-segment estimation from keypoint correspondences · RANSAC · cv2.recoverPose

How extrinsics were estimated

Extrinsic parameters (R, t) describe the relative position and orientation between cameras. Here they were estimated per segment from 2D keypoint correspondences using the Essential Matrix approach — more robust to real-world camera placement uncertainty than a fixed geometric model.

```
P_A = [I|0]   P_B = [R|t]   →   points4D = cv2.triangulatePoints(P_A, P_B, ptsA.T, ptsB.T)
```

- **Undistort keypoints:** cv2.undistortPoints() applied to both cameras — removes lens distortion before geometry estimation.
- **Essential Matrix E:** cv2.findEssentialMat() with RANSAC (prob=0.999, threshold=1e-3) — automatically filters outlier correspondences.
- **R and t recovery:** cv2.recoverPose() from RANSAC inliers → R and t. Camera pair used: decubit_dorsal1/2 → cam1+cam2 · decubit_scurtat / ortostatism → cam2+cam3.
- **Limitation:** Stereo pair only (2 cameras per segment) — no trifocal constraint. [illegible]



*Hartley R, Zisserman A. Multiple View Geometry in Computer Vision. 2nd ed. Cambridge University Press; 2003
*Zhang Z. IEEE Trans PAMI. 2000;22(11):1330-1334

Step 4 — 2D Keypoint Extraction

Step 4/6

MediaPipe Holistic · 36 landmarks per frame · confidence filtering

MediaPipe Holistic — how it works

Single-pass neural network processes each video frame and simultaneously detects pose landmarks (33 pts) and hand landmarks (21 pts/hand). For LL analysis we use 36 targeted landmarks — the shared 34 from UL plus knee_left and knee_right.

Landmark	Index	Use in LL analysis
Shoulders	idx 11–12	Reference frame for upper body position
Elbows / Wrists	idx 13–16	Included from shared protocol
Hips	idx 23–24	Pelvis anchor — critical for M1, M4 hip flexion
Knees	idx 25–26	Primary LL joint — all 5 movements
Ankles	idx 27–28	M3 dorsiflexion · M5 heel endpoint
Hand landmarks	idx 0–20 (R)	Shared from UL — not used in LL analysis



Confidence filtering

Threshold ≥ 0.5 applied per landmark per frame. Frames with low-confidence landmarks flagged — not discarded, but excluded from kinematic calculations.

Env › Intrinsic › Extrinsic › **Keypoints** › DLT › Export

*Lugaresi C, et al. MediaPipe: A Framework for Building Perception Pipelines. arXiv:1906.08172. 2019
*Zhang Z. IEEE Trans PAMI. 2000;22(11):1330-1334

Step 5 — 3D Reconstruction via Stereo Triangulation

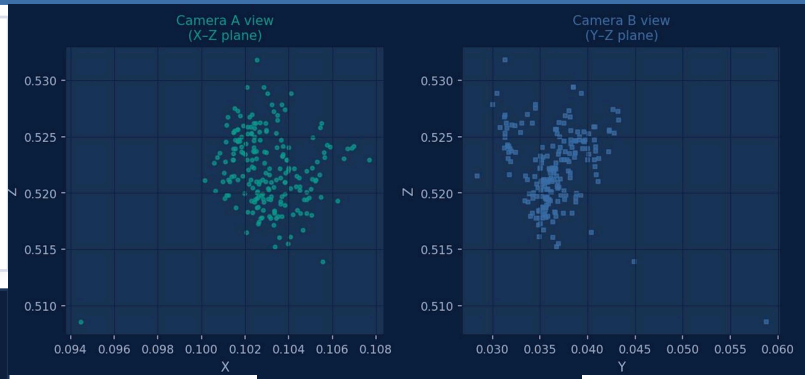
Step 5/6

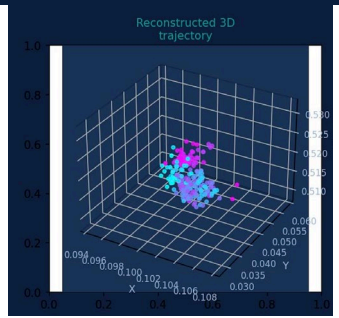
cv2.triangulatePoints · stereo pair per segment · homogeneous coordinates

How triangulation works here

Given 2D keypoint positions in two calibrated camera views and their projection matrices P_A, P_B, OpenCV's triangulatePoints() solves for the 3D position. Result is in homogeneous coordinates [X,Y,Z,W] — divided by W to get Cartesian 3D. Only RANSAC inliers from Step 3 are used.

```
points4D = cv2.triangulatePoints(P_A, P_B, ptsA.T, ptsB.T)
points3D = (points4D[:3, :] / points4D[3, :]).T   # N × 3
# applied per segment · only RANSAC inliers · stereo pair
```





Only RANSAC inliers:	Correspondences that failed Essential Matrix RANSAC are excluded before triangulation — reduces 3D noise from outlier matches.
Stereo pair, not trifocal:	2 cameras per segment only. Lower redundancy than 3-camera DLT but sufficient for gross joint angle analysis.
Output:	X, Y, Z in normalized camera-A space per landmark per frame — stored in joints3d_all_segments.csv.

Env › Intrinsic › Extrinsic › Keypoints › **DLT** › Export

*Hartley R, Zisserman A. Multiple View Geometry in Computer Vision. 2nd ed. Cambridge University Press; 2003
*Savitzky A, Golay MJE. Anal Chem. 1964;36(8):1627-1639

Step 6 — Smoothing, Export & Dataset

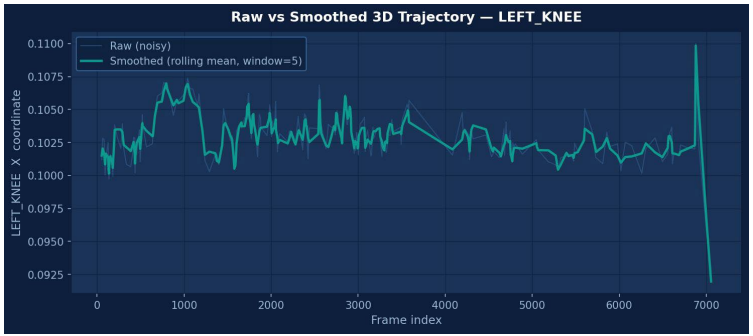
Step 6/6

Rolling mean filter (window=5) · structured CSV · LL dataset statistics

Rolling Mean Smoothing

Raw 3D coordinates contain frame-to-frame jitter from pose estimation noise. A centered rolling mean (window=5 frames) averages each coordinate over its temporal neighbourhood — simple and effective for suppressing high-frequency noise in gross joint angle analysis.

```
j["X"] = j["X"].rolling(5, center=True,
min_periods=1).mean()
```



5	5×	36	~65k
LL movements recorded	severity levels per movement	landmarks per frame	rows in LL dataset

CSV structure `frame_rel, joint, X, Y, Z` · one row per landmark per frame · separate file per movement/severity

Env › Intrinsic › Extrinsic › Keypoints › DLT › **Export**

*Savitzky A, Golay MJE. Smoothing and differentiation of data. Anal Chem. 1964;36(8):1627-1639
*Virtanen P, et al. Nat Methods. 2020;17:261-272
*Drillis R, Contini R. NYU; 1966

M1 — Volitional Movement within Synergy · 3-Camera Demo

Supine · hip/knee/ankle within extensor synergy · earliest voluntary motor control (Brunnstrom Stage 2–3)

FMA Protocol — M1

Movement
Hip flexion + knee flexion + ankle dorsiflexion within extensor synergy pattern

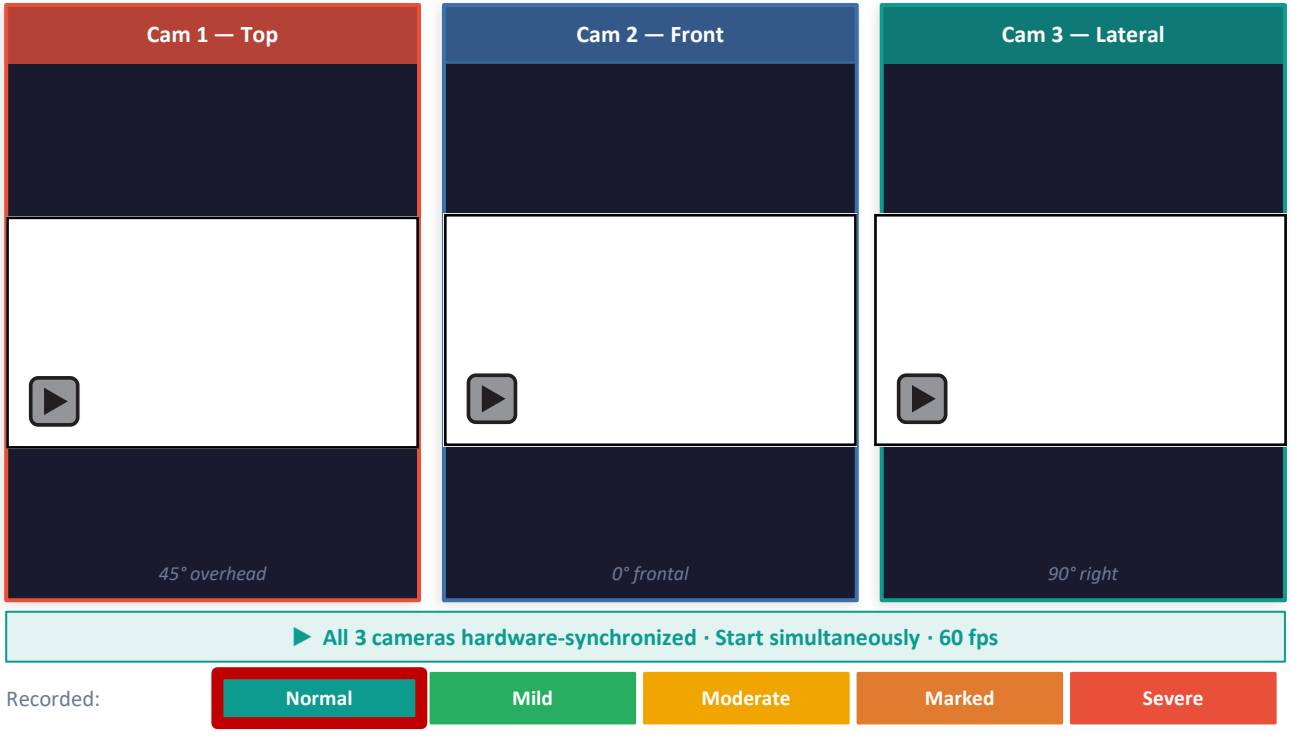
Position
Supine

Instruction
"Flex your hip and knee as high as possible"

Tests
Earliest voluntary motor control.
Brunnstrom Stage 2–3

Scoring
0 = cannot initiate
1 = partial movement
2 = full synergy pattern

Clinical note
Synergy pattern = all 3 joints move together — cannot be isolated



*Fugl-Meyer AR, et al. Scand J Rehabil Med. 1975;7(1):13-31
*Brunnstrom S. J Am Phys Ther Assoc. 1966;46(4):357-375
*Onose G, et al. Front Neurol. 2023;13:1022546

M5 — Heel-to-Knee Coordination · 3-Camera Demo

Supine · 5 repetitions · tremor · dysmetria · movement speed — Brunnstrom Stage 6

FMA Protocol — M5

Movement
Heel placed on opposite knee, slide down shin to ankle — repeated 5 times

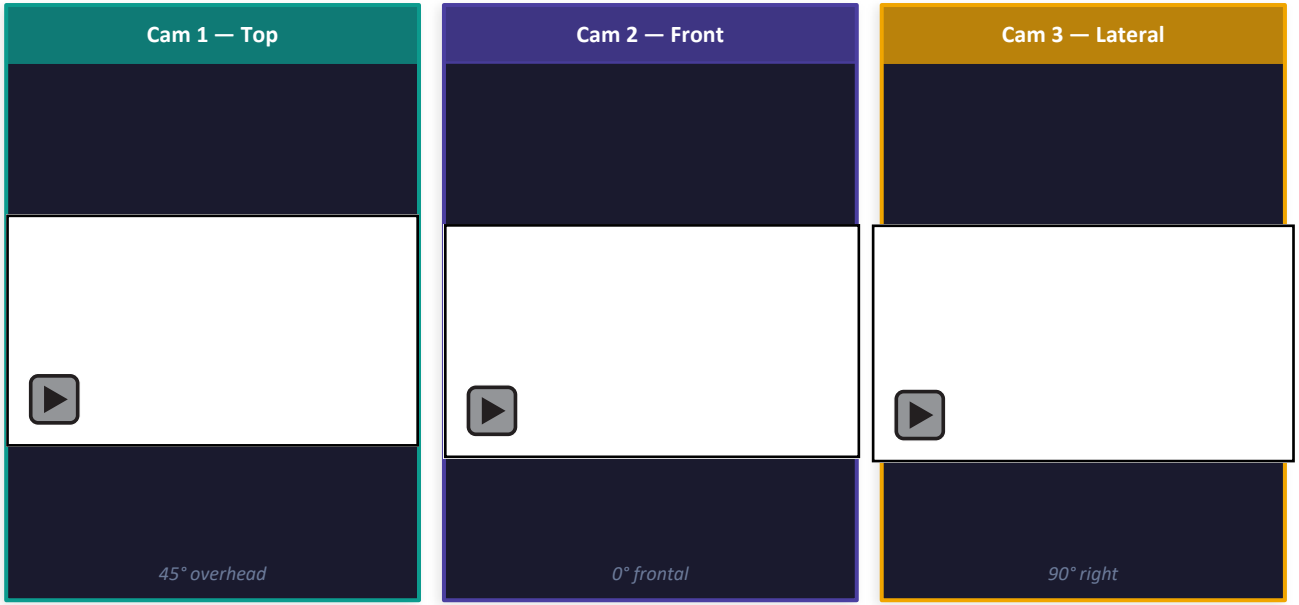
Position
Supine

Instruction
"Place your heel on your knee and slide down to your ankle, 5 times"

Tests
Coordination, dysmetria, tremor, movement speed (Brunnstrom Stage 6)

Scoring
0 = no coordination
1 = partial or tremulous
2 = smooth and precise

Clinical note
Jerk metric quantifies tremor from velocity curve — invisible to naked eye



▶ All 3 cameras hardware-synchronized · Start simultaneously · 60 fps

Heel landmark trajectory · deviation from straight line · velocity profile + jerk metric — tremor and movement fragmentation quantified frame by frame

Fugl-Meyer AR, et al. Scand J Rehabil Med. 1975;7(1):13-31
Savitzky A, Golay MJE. Anal Chem. 1964;36(8):1627-1639
Onose G, et al. Front Neurol. 2023;13:1022546

Kinematic Output — What the Data Looks Like

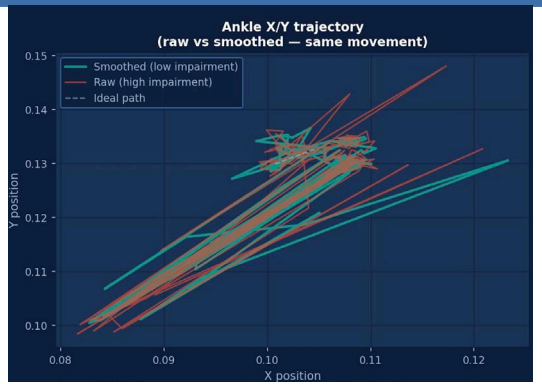
From 3D coordinates to clinically interpretable movement curves

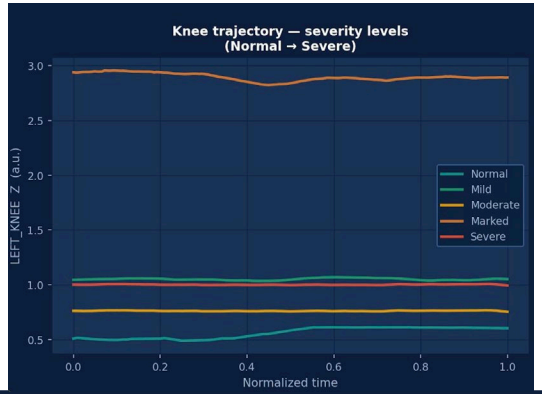
What we extract per movement

- **Joint angle time series:** Knee flexion angle (degrees) at every frame — 60 measurements per second
- **Range of motion:** Maximum and minimum angle reached — quantified without a goniometer
- **Velocity profile:** Speed of joint movement — reveals hesitation, tremor, synergy pattern
- **Deviation from Normal:** Difference between patient trajectory and Normal reference level

The clinical parallel

What you observe as "knee doesn't flex beyond 90°" becomes a time series with a peak of 76° in mild vs 31° in severe — same clinical judgment, now with a number attached.





Drillis R, Contini R. Body Segment Parameters. NYU; 1966
Savitzky A, Golay MJE. Anal Chem. 1964;36(8):1627-1639
Fugl-Meyer AR, et al. Scand J Rehabil Med. 1975;7(1):13-31

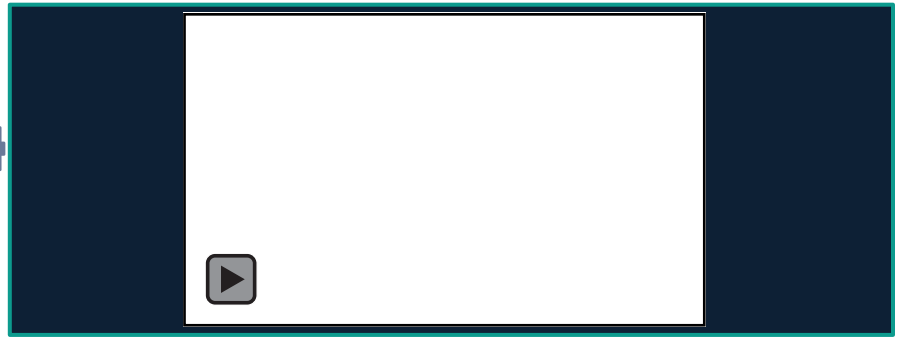
From Raw Video to 3D Skeleton — Proof of Concept

Markerless pose estimation · 3D joint reconstruction · qualitative validation

Raw video — camera view

Reconstructed 3D skeleton









Qualitative validation: skeleton geometry is anatomically plausible across all segments · joint trajectories are temporally stable · 3D structure is consistent with observed movement

Lugaresi C, et al. arXiv:1906.08172. 2019 · Hartley R, Zisserman A. Multiple View Geometry. Cambridge UP; 2003

Anatomical Validation — LL Dataset

Geometric plausibility check · scale recovery required for metric validation

4	2	11	~65k
segments recorded	cameras per segment	joints tracked	rows in LL dataset

Validation check	Status	Notes
Skeleton plausibility — visual	✓ Confirmed	3D joint positions form anatomically coherent skeleton across all segments
Landmark continuity — temporal	✓ Confirmed	Joint trajectories are smooth and continuous — no major dropout across segments
Metric segment lengths (cm)	⚠ Not applicable	Essential Matrix recoverPose() returns t at unit scale — coordinates are not metric. Scale recovery required.
Segment length ratios	⚠ Inconsistent	Ratios vary significantly across segments (arbitrary scale per segment) — not comparable to physical reference
Validation vs Vicon / marker system	○ Deferred	Planned for Phase 1 — simultaneous markerless + optical recording with scale calibration

Why metric validation is not possible here

cv2.recoverPose() normalises the translation vector to unit length — meaning 3D coordinates are in arbitrary units, not metres. Each segment has its own unknown scale. Metric validation requires either physical scale markers in the scene or simultaneous checkerboard calibration (Phase 1).

Hartley R, Zisserman A. Multiple View Geometry. Cambridge UP; 2003 · Drillis R, Contini R. NYU; 1966 · Fugl-Meyer AR, et al. Scand J Rehabil Med. 1975;7(1):13-31

From Clinical Observation to Digital Measurement — LE

What the clinician observes · What the camera quantifies

Clinical observation	Digital measurement
Clinician watches synergy pattern	3D joint angles per frame, deviation from normal trajectory
Knee doesn't flex beyond 90°	Knee angle time series — max flexion quantified in degrees at every frame
Hip flexion incomplete or compensated	Hip landmark trajectory — vertical displacement and range of motion vs Normal reference
Ankle doesn't dorsiflex actively	Ankle angle curve — dorsiflexion amplitude and movement speed profiled continuously
Patient trembles during heel-to-knee	Velocity — tremor and movement fragmentation quantified from speed curve

Current Limitations

Honest assessment of constraints — and why they don't invalidate the framework

Single-subject dataset (n=1) — High

All movements performed by one skilled physiotherapist simulating 5 severity levels. Provides proof-of-concept and reference dataset, but not clinical generalizability. Multi-subject recording with actual patients is the next step.

No ground truth validation — Medium

Pipeline not yet validated against optical marker systems (Vicon, Qualisys). Geometric calibration introduces ~8% error in some segments. Simultaneous checkerboard calibration planned.

Per-segment extrinsic estimation — Medium

Extrinsics estimated per-segment via Essential Matrix + RANSAC from keypoint correspondences — not from physical measurements. R and t valid only relative to camera A origin, not a world coordinate frame.

Occlusion in supine/sitting — Low–Med

Lateral camera view partially blocked in supine and sitting positions — affects ankle and lower leg landmark confidence in M1, M3, M5. Confidence filtering applied but some frames excluded.

Left hand/limb partial tracking — Low

Some movements show reduced landmark confidence on the contralateral limb — inherent limitation of RGB-only markerless systems without depth information.

Needham L, et al. J Biomech. 2022;138:111112
Wishaupt K, et al. Sci Rep. 2024;14:11910
Zhang Z. IEEE Trans PAMI. 2000;22(11):1330-1334

Next Steps — Toward Clinical Translation

From proof-of-concept to validated rehabilitation tool

Multi-subject recording

Phase 1

Patients with confirmed post-stroke UE and LE hemiparesis + healthy controls. Target: ≥10 subjects per severity level.

Validation vs Vicon

Phase 1

Simultaneous markerless + optical marker-based recording. Quantify per-landmark 3D error across movements and severity levels.

Simultaneous checkerboard calibration

Phase 1

Replace geometric extrinsic estimation with synchronized multi-camera calibration — expected to reduce segment error from ~8% to <3%.

LSTM Autoencoder — automated scoring

Phase 2

Train on Normal reference recordings. Reconstruction error = deviation score. Classify severity level automatically from kinematic input.

Compensation detection

Phase 2

Latent space analysis to distinguish true motor recovery from compensatory strategies. Segment-specific deviation flagging.

Telerehabilitation integration

Phase 3

Remote assessment module — patient records at home, system scores automatically against Normal reference and alerts clinician to changes.

*Tannús J, et al. npj Digit Med. 2026
*Unger T, et al. arXiv:2411.14992 (2024)
*Wishaupt K, et al. Sci Rep. 2024;14:11910

”postural control and movement accuracy. Snowball Fight can be played individually or with a partner. In individual mode, the patient plays against a computer-controlled enemy penguin that is throwing snowballs at the patient. If played with a partner, the partner plays the role of the enemy penguin.

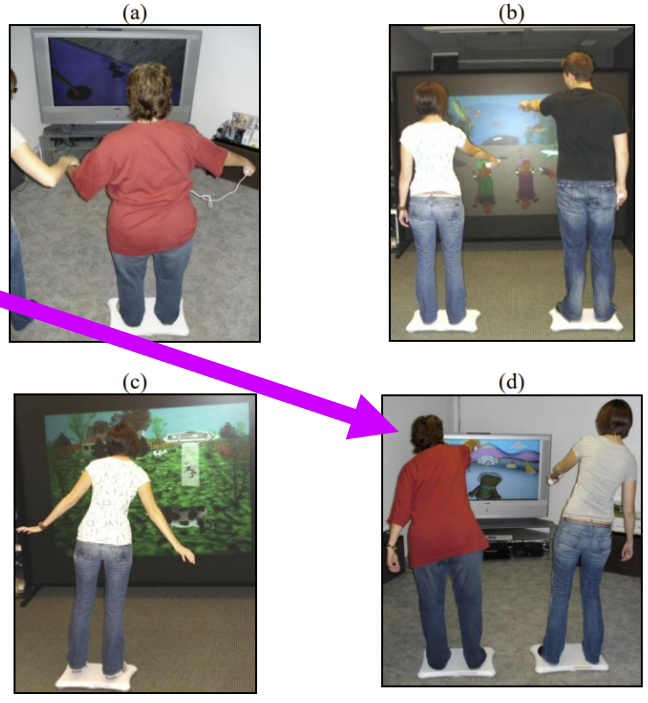


Figure 1: Patients interacting with: a) Mouse House, b) Startle Fish, c) Alien Invasion, d) Snowball Fight

In the Mouse House activity, the patient plays the role of a mouse that searches through a large virtual house to find pieces of cheese. In this activity, the patient uses a Wii Balance Board and a Wii Remote. The patient can sit on, stand on, or kneel on the Balance Board and use it as a navigation interface by shifting their weight to move the virtual mouse. This activity challenges the patient to exercise balance and movement precision. This activity can be played individually or with a partner. In partner mode, ...”*

*Anderson F, Annett M, Bischof WF. Lean on Wii: physical rehabilitation with virtual reality Wii peripherals. Stud Health Technol Inform. 2010;154:229-34. PMID: 20543303.

Conclusions — Part II

StratifAI · Lower Extremity · Markerless 3D · FMA Paradigm

The same markerless 3D pipeline developed for UE in Part I was successfully applied to all 5 FMA-LE movements across 5 severity levels in the lower extremity

Position-dependent recording (supine · sitting · standing) introduces higher occlusion risk than UE, requiring camera angle optimization per body position

Only 2 additional landmarks required (knee_left, knee_right) — demonstrating the scalability of the shared 34-landmark protocol to LE analysis

Kinematic data (joint angles, velocity profiles, heel trajectories) is stored and ready for downstream analysis — including automated FMA scoring and compensation detection

The Normal reference level provides the essential digital twin baseline for future deviation scoring — without it, there is nothing to compare the patient against


CONSTRUIRE,
C'EST UN DON...
THANK YOU
FOR YOUR
ATTENTION !