SymStride

Michael, Ido, Yibo

Motivation

Novice to intermediate runners tend to get hurt often when beginning to run, often because they do not have access to a coach.

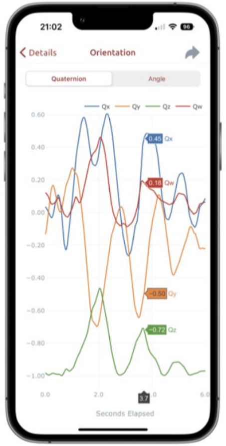
There are a few products that work to solve this problem, some using video to analyze running and others using specialized IMU sensors.

Motivation

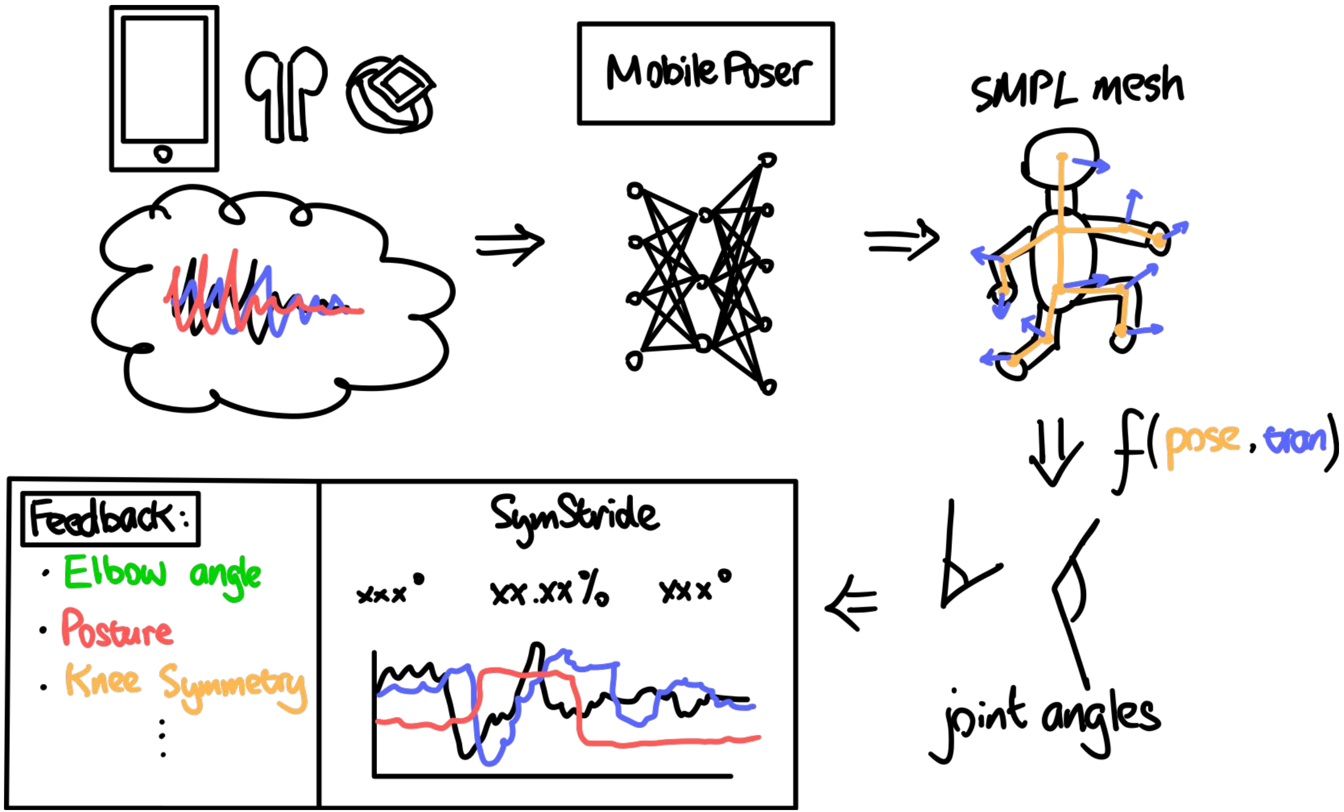
Our literature review uncovered that the company *Ochy* is the leading running analysis provider without specialized hardware.

However, Ochy is limited to the size of your frame.

Is it possible to use on-body sensors instead of being limited by camera-based vision?



SymStride — System Design



Methodology

Core Geometry & Angle Calculation

Normalize both Vectors

$$\hat{V}_1 = \frac{V_1}{\|V_1\| + \epsilon}, \quad \hat{V}_2 = \frac{V_2}{\|V_2\| + \epsilon}$$

Compute clamped dot product

$$d = \mathrm{Clamp}(\hat{V}_1 \cdot \hat{V}_2, -1, 1)$$

Joint Angle = interior angle between Segments

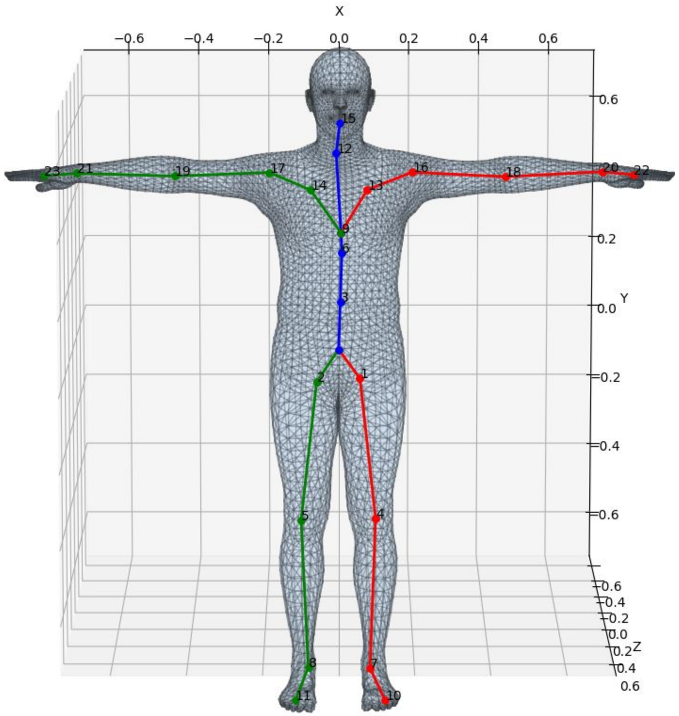
$$\theta = \arccos(d), \quad \theta_{deg} = \theta \cdot \frac{180}{\pi}$$

- Build two 3D vectors from the joint of interest to its neighbors (knee -> hip & knee -> ankle)
- Normalize both vectors
- Compute clamped dot product for numerical stability
- Joint angle = interior angle between segments

Knee + Elbow Angles (left/right)

SMPL (skinned multi-person linear model)

- We get join positions: Hip, knee, ankle, etc... (SMPL-indexed)
- For each side:
    - Vector from knee to hip = hip - knee
    - Vector from ankle to knee = ankle -knee
    - Knee angle = angle between these two vectors (hip-knee interior angle)
- Similar logic for elbow joint angles
    - Vector from elbow to shoulder
    - Vector from elbow to wrist
    - Elbow angle = interior angle between these 2 vectors



Front vs Back Leg Classification

1. Velocity based
   - Pelvis velocity: Vtravel = Pelvis(current) - Pelvis (prev)
   - Project feet (relative to pelvis) onto travel direction vector

$$p_L = (\text{L\_FOOT} - \text{Pelvis}) \cdot \hat{v}_{\text{travel}}, \quad p_R = (\text{R\_FOOT} - \text{Pelvis}) \cdot \hat{v}_{\text{travel}}$$

   - Foot with larger projection = front leg, other = back leg.

2. Knee - Extension Fallback
   - Compare left vs right knee angles
   - More extended (larger angle) = front leg (more biomechanically correct)

Head Tilt and Lean

Head Tilt/ Back-to-head angle

1. Vectors:
   a. Pelvis-to-head vector: Head - Pelvis
2. Method:
   a. Project onto the YZ plane (sagittal plane) using SMPL coordinates:
      i. Y: vertical (up-down)
      ii. Z: forward / back
   b. Compute angle from vertical using atan2 (x = atan2(z,y), angle of head direction from vertical)

Lean captures bend of the spine using a 3-segment model:

1. Vectors:
   a. Pelvis to upper spine (spine3): Vps3 = Spine3 - Pelvis
   b. Upper spine to head: Vs3h = Head - spine3

- Spine Curvature/Lean = interior angle between Vps3 and Vs3h via the same dot product/acos routine previously mentioned.

Foot Landing Detection (and why we don’t trust it yet)

We detect candidate foot landings from SMPL joints using:

- Foot/ankle height minima
- **Vertical velocity zero-crossing** (downward -> stopped ascending)
- Proximity to an estimated ground level (from low-percentile foot heights)

In theory, this should mark heel strikes and let us measure angles “at landing”

In practice, IMU-only pose is currently too jittery and absolute heights are unreliable.

- Landing frames are noisy and inconsistent

For SymStride, we don’t use landing-based metrics and instead report global average angles over the whole run

Evaluation

Experimental Evaluation

- **Goal:** Matching our IMU derived metrics to vision derived metrics in Ochy
- **Approach:**
  - 3 trials each for each of the three team members
  - Run the same motion through both systems (Ochy and our IMU pipeline)
  - Compare the resulting joint angles
  - Compare the higher level insights (Good, Okay, Bad)
- **Success Criteria:**
  - Small differences between IMU derived joint angles and Ochy's measurements
  - Generally consistent high level insight and feedback

Metric	SymStride Mean±SD	Ochy Mean±SD	Mean Diff	MAD	Feedback Agreement
Front Knee	144.7±4.3°	151.2±6.6°	-6.5°	7.8°	88.9%
Back Knee	146.2±4.3°	115.7±7.9°	***+30.6°****	***30.4°****	0%
Elbow Flexion	123.3±6.5°	120.3±20.0°	+2.9°	20.6°	100%
Gaze	-1.1±1.9°	-6.8±7.3°	+5.7°	8.0°	22.2%
Lean	8.8±1.3°	6.9±4.4°	***+1.9°****	3.9°	66.7%

Statistically significant (|t| > 4.303)

Key Findings

- **Back Knee** shows the largest systematic difference (30.6°) and complete feedback disagreement
  - This is likely due to the fact that the model does not generalize well for heel drive as the training data does not show diversity
- **Elbow Flexion** has perfect feedback agreement despite high Ochy variability (CV=16.6%)
  - Likely biased due to more open elbow positions across all three individuals
- **SymStride** is more consistent across all metrics (lower CVs) compared to Ochy
- **Gaze** has poor agreement (22%) despite both systems measuring it
  - Likely due to the larger proximity from the phone; harder for the model to capture those nuances in our current set-up

Future Work + Conclusion

- Improving model accuracy and fine-tuning the model for running
- Adding Apple Watch and AirPods into the ecosystem to improve metrics like gaze and elbow flexion
    - Working intimately with the model inference and setting up our own modules to work with our own devices

- Elbow flexion cannot be reasonably detected without Apple Watch integration
- Foot landing is difficult to analyze from SMPL sequences
- **SymStride is more consistent compared to Ochy**
- **Actionable feedback is largely consistent with Ochy**

References

V. Xu, C. Gao, H. Hoffmann, and K. Ahuja, “MobilePoser: Real-Time Full-Body Pose Estimation and 3D Human Translation from IMUs in Mobile Consumer Devices,” Human-Computer Interaction, pp. 1–11, Oct. 2024, doi: 10.1145/3654777.3676461.

Van Hooren, B., Goudsmit, J., Restrepo, J., & Vos, S. (2020). Real-time feedback by wearables in running: Current approaches, challenges and suggestions for improvements. Journal of Sports Sciences, 38(2), 214–230. https://doi.org/10.1080/02640414.2019.1690960

Y. Huang, M. Kaufmann, E. Aksan, M. J. Black, O. Hilliges, and G. Pons-Moll, “Deep Inertial Poser: Learning to Reconstruct Human Pose from Sparse Inertial Measurements in Real Time,” arXiv.org, Oct. 10, 2018. https://arxiv.org/abs/1810.04703

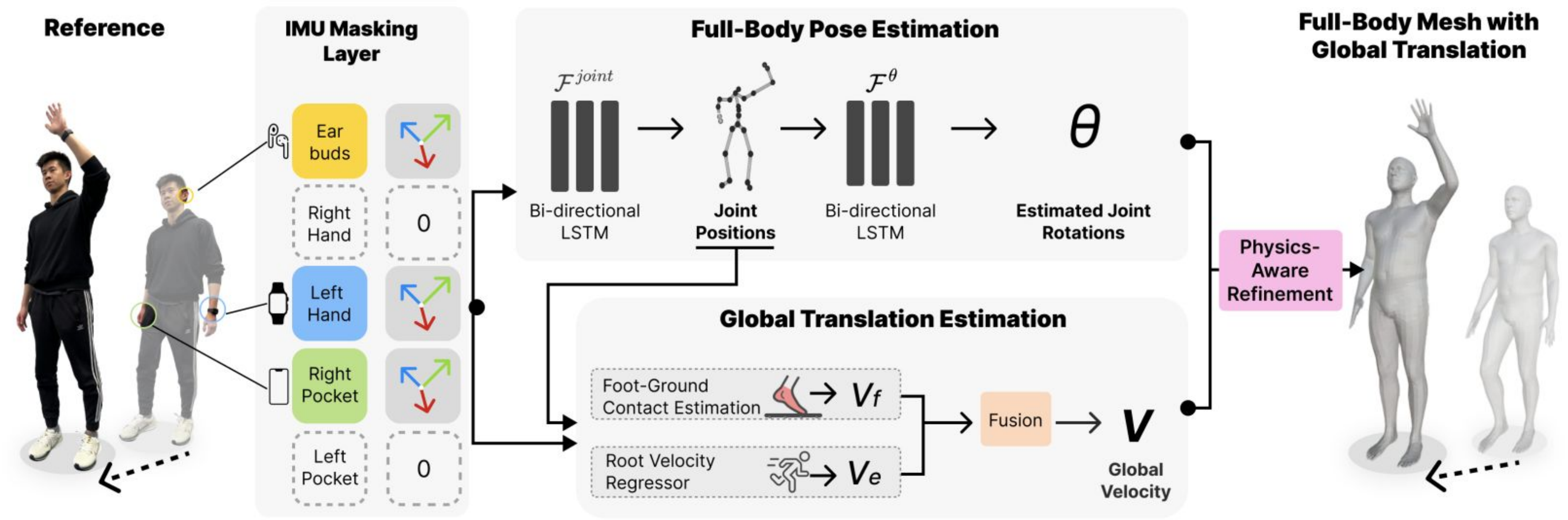
Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., & Black, M. J., “SMPL: A Skinned Multi-Person Linear Model,” ACM Trans. Graphics, vol. 34, no. 6, pp. 248:1–248:16, Oct. 2015.

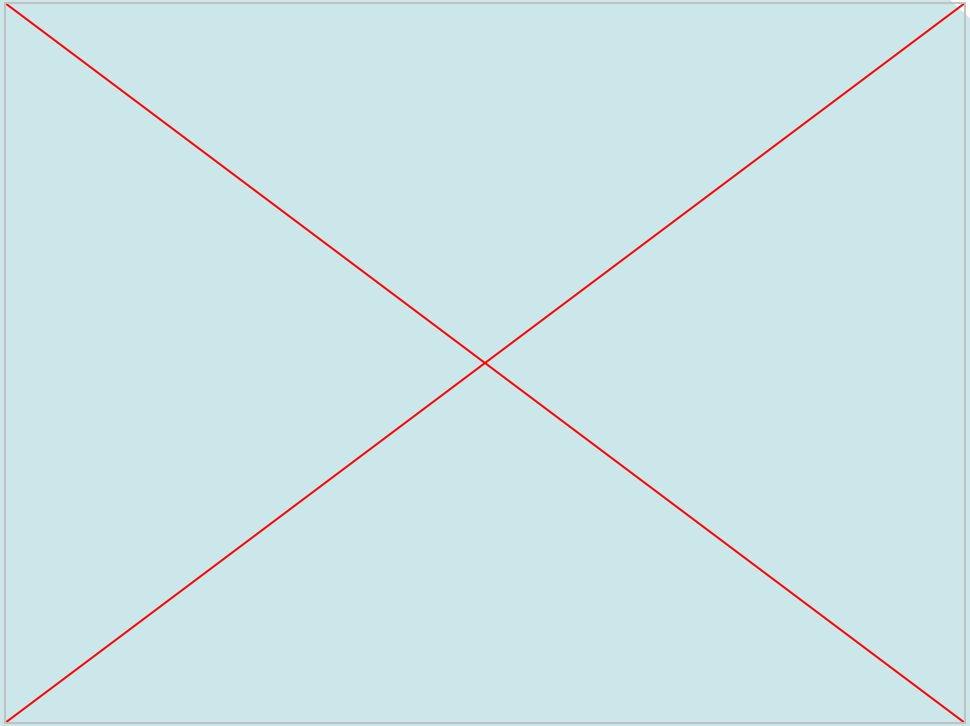
V. Mollyn, R. Arakawa, M. Goel, C. Harrison, and K. Ahuja, “IMUPoser: Full-Body Pose Estimation using IMUs in Phones, Watches, and Earbuds,” N/A, pp. 1–12, Apr. 2023, doi: 10.1145/3544548.3581392.

N. Mahmood, N. Ghorbani, N. F. Troje, G. Pons-Moll, and M. J. Black, “AMASS: Archive of Motion Capture as Surface Shapes,” in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), Oct. 2019, pp. 5442–5451

Thank you!


Feedback


Reference
IMU Masking Layer
Ear buds
Right Hand
0
Left Hand
Right Pocket
Left Pocket
0
Full-Body Pose Estimation
$\mathcal{F}^{joint}$
Bi-directional LSTM
Joint Positions
$\mathcal{F}^{\theta}$
Bi-directional LSTM
θ
Estimated Joint Rotations
Global Translation Estimation
Foot-Ground Contact Estimation
V_f
Root Velocity Regressor
V_e
Fusion
V
Global Velocity
Physics-Aware Refinement
Full-Body Mesh with Global Translation



Potential Questions

- What does calibration do?
- How is the model creating the pose?
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