

WiFi as a sensor

A WiFi packet never arrives untouched: it reflects off walls, scatters off furniture, and bends around people. The receiver already measures that distortion to decode data so the same hardware can double as a sensor, telling walking from falling or counting breaths, with no cameras or wearables [1, 10, 12].

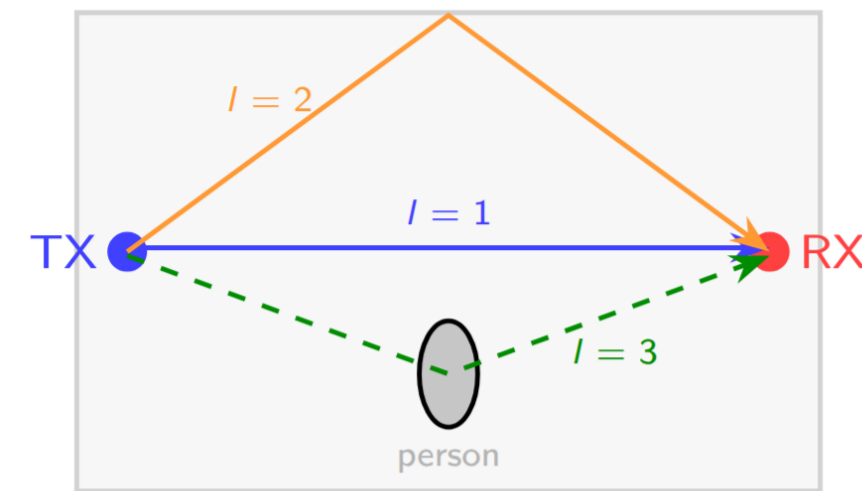


Figure 1. Direct, wall-bounce and body-scattered paths ($l=1, 2, 3$) sum at the receiver, each with its own attenuation and delay.

The received signal sums over all propagation paths,

$$r(t) = \sum_{l=1}^L a_l s(t - \tau_l),$$

with per-path attenuation $a_l \in \mathbb{C}$ and delay τ_l . Move anything in the room and the a_l, τ_l shift.

CSI: the channel's fingerprint

WiFi exposes this distortion as Channel State Information (CSI) the channel's frequency response at each subcarrier f_k , for every Tx-Rx antenna pair (n, m) and packet time t :

$$H(n, m, f_k, t) = \sum_{l=1}^L a_l(t) e^{-j2\pi f_k \tau_l(t)}.$$

Stacked over antennas, subcarriers and time, a 4D tensor $H \in \mathbb{C}^{N \times M \times K \times T}$ (5.785 GHz, $\Delta f = 312.5$ kHz, $K = 114$).

A moving body part changes its path length at rate \dot{d} , sliding that path's phase at a Doppler frequency $f_D = \dot{d}/\lambda$. Limbs and torso move at different speeds, so a motion smears into a *band* of shifts its micro-Doppler signature [3].

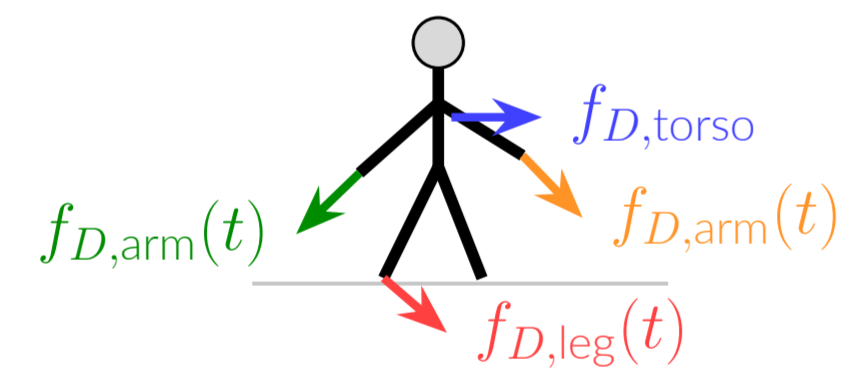


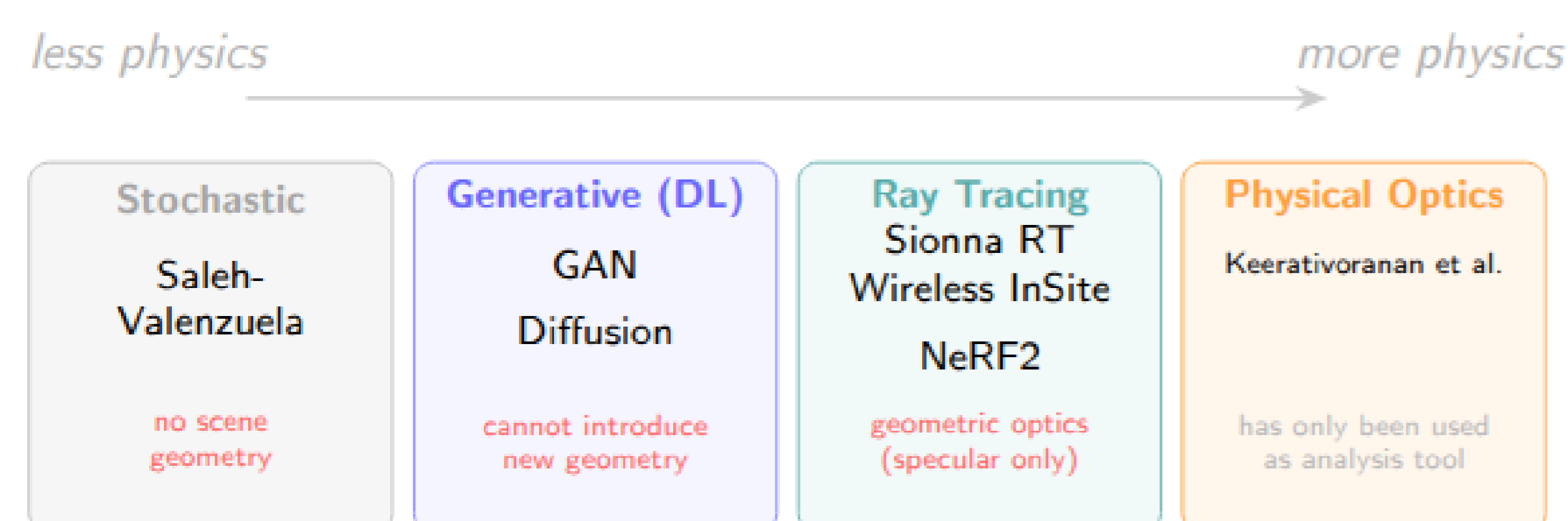
Figure 2. Each part writes its own time-varying f_D , their sum is the time-Doppler pattern sensing reads.

The catch: geometric overfitting

The channel is tied to the room's exact layout, so a model trained in one room often collapses in another, moving a device or the subject can suffice [7, 16, 11, 6]. Robust sensing needs data over many geometries, far more than anyone can measure.

Physical knowledge as a way out

Two ways to inject physics: bake physical descriptors into the pipeline (angle, delay, Doppler, geometry-aware features [14, 13, 6]), or use a physical model to generate synthetic CSI for training. The second is the bigger prize, simulate any scene and the data bottleneck disappears.



What is physical optics?

PO sits between geometric optics, fast, but limited to mirror-like specular rays with no diffraction, and full-wave solvers such as FDTD, near-exact, but far too slow for a moving scene [9, 15]. PO models each lit surface as a sheet of induced currents, so its scattered field varies smoothly with geometry instead of snapping between discrete rays [2, 4].

Setup: a twin dataset

One actor performs labelled activities while WiFi (1 Tx, 3 Rx \times 4 antennas) and a motion-capture rig record simultaneously. MoCap markers are fit to a 19-ellipsoid body model that drives the PO forward model of Keerativoranan et al. [8] under the identical Tx-Rx geometry a real and a simulated twin of the same event.

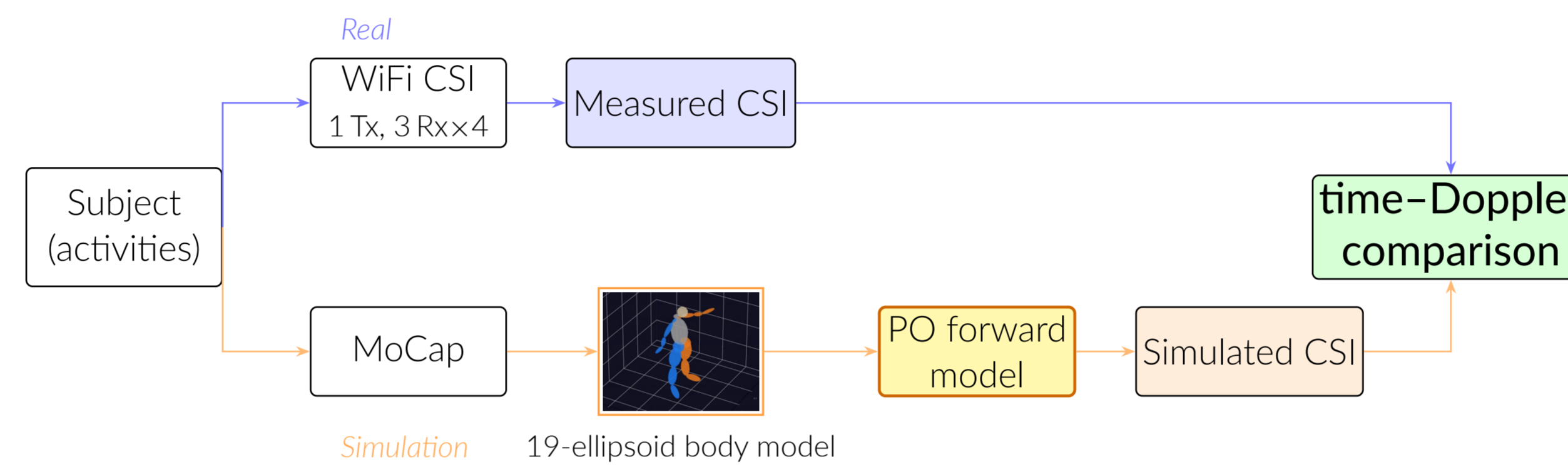


Figure 3. Same actor, motion, antennas and clock. Hardware artefacts make raw CSI incomparable, so we compare in the time-Doppler domain.

Research aim

Main RQ: Can a PO forward model, with no learned components, produce WiFi CSI useful for sensing?

- **RQ1:** does it look right (time-Doppler)?
- **RQ2:** is it measurably close?
- **RQ3:** does a model trained on it *transfer* to real data?

RQ1: does it look right?

At first glance, yes. Both share the static ridge at $f_D=0$ and burst into Doppler spread exactly when the actor moves. But the texture differs: the real spectrogram drifts smoothly, while the simulated one flickers, power leaping across frequencies between neighbouring instants.

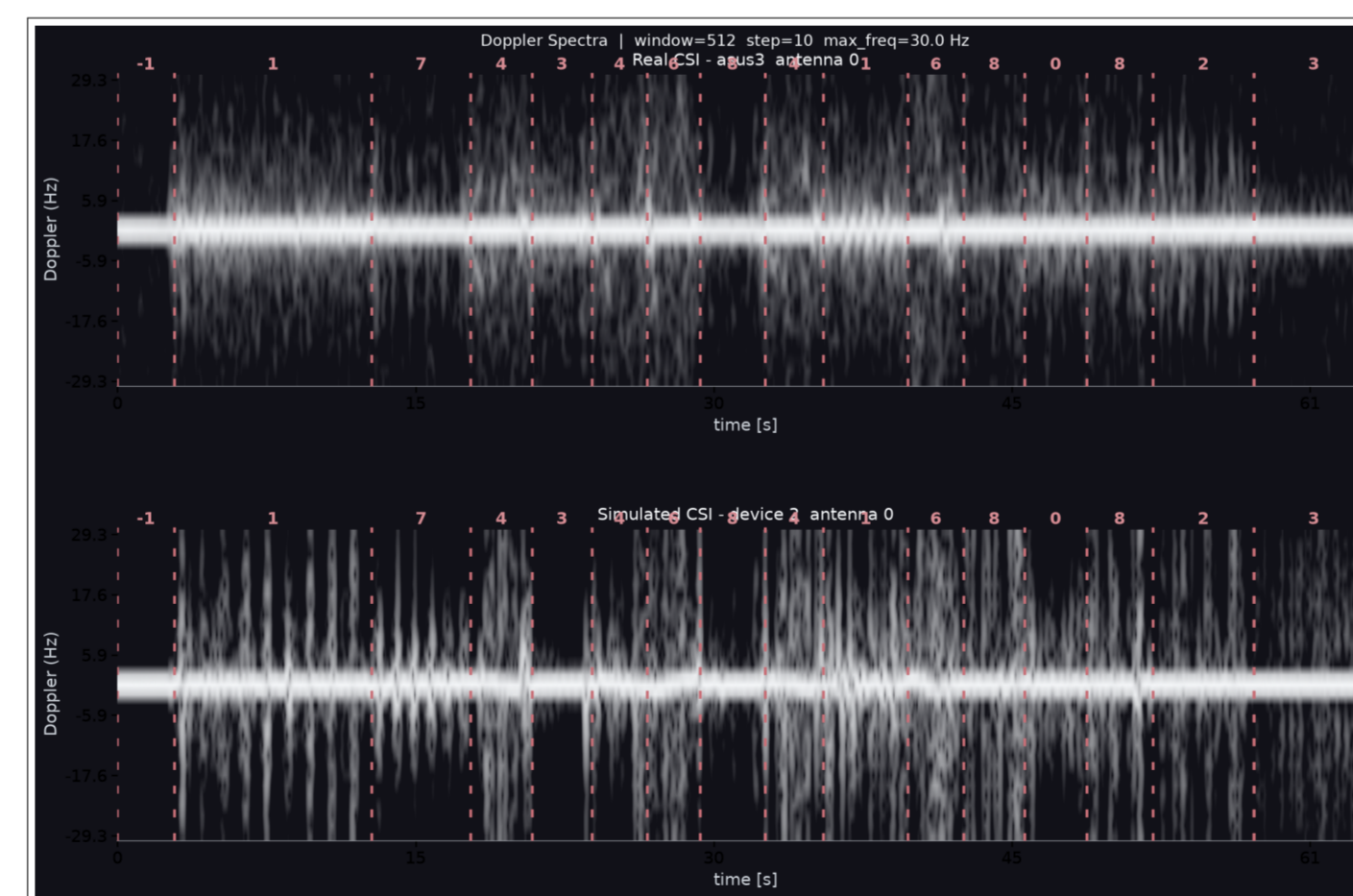


Figure 4. Time-Doppler spectrograms: real (top) vs simulated (bottom), same recording. Dashed lines mark activity boundaries.

Each of 19 body segments adds a single specular bounce. Real bodies also scatter diffusely, diffract and carry noise, all of which smear power smoothly.

RQ2: is it close enough?

We train a classifier to label each frame *real* or *simulated*. If the two were interchangeable it would be stuck at chance, 0.50. Instead:

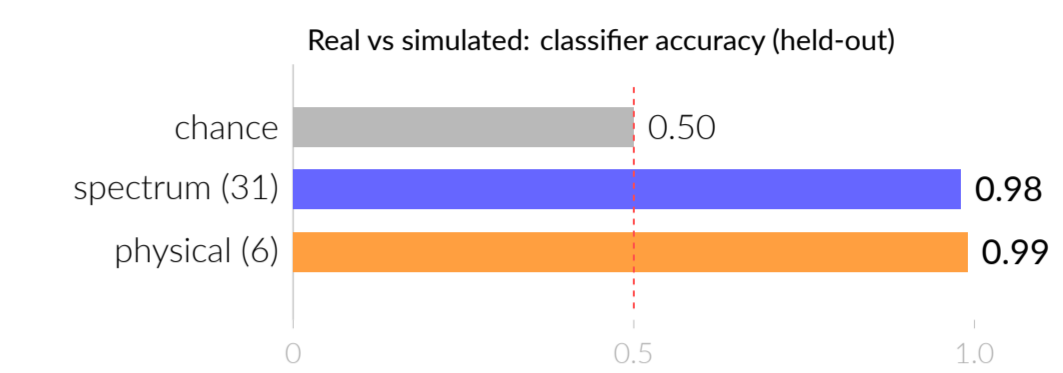


Figure 5. Both feature sets separate the streams near-perfectly; a model-free MMD test agrees. Shuffled-label control sits at 0.50.

The differences are not random detail a model can ignore, they are systematic, the very shortcut a sensing model would take instead of learning the transferable signal.

Conclusion

PO reproduces the gross micro-Doppler structure, matching the qualitative validation of Keerativoranan et al. [8], but it is not yet a stand-in for real CSI. A classifier separates the two almost perfectly, so synthetic-only training stays unreliable until the gap closes (RQ3).

Future work: close the gap

Keep the physics for the geometry it gets right, and learn a correction from simulated spectrograms to real ones: a paired image-to-image translation [5] over whole activity segments, not single frames, the gap lies in how the signal *evolves over time*.

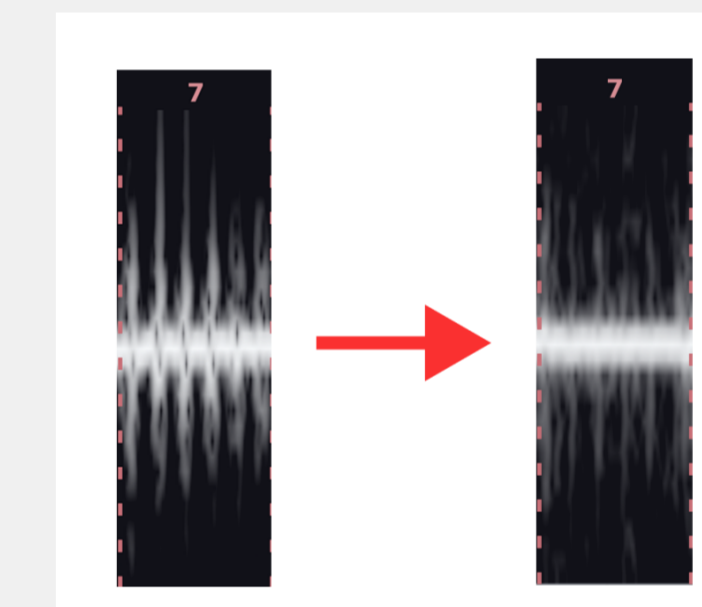


Figure 6. Learn simulated \rightarrow real, per activity segment.

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