Synthesized Millimeter-Waves for Human Motion Sensing

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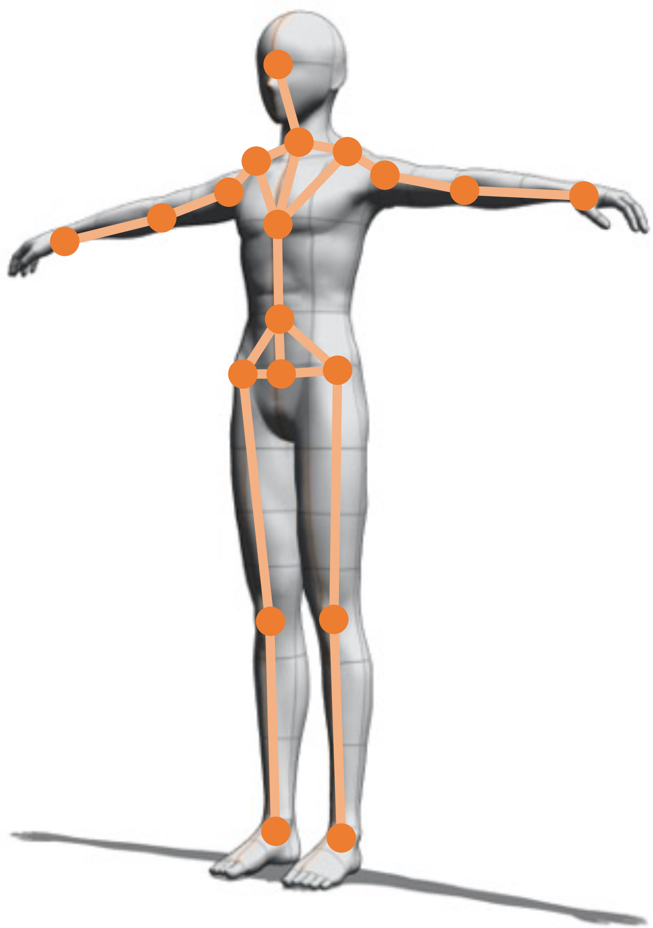
Sensing Human Motion



- Meaning of this activity?

  Activity Recognition

- How does the body move?

  Skeleton Tracking

- Which solution to use?

  mmWave, Wi-Fi, Wearable…

Sample Pictures
play slide show
by name
by date
by rating
Hydrangeas
SAMSUNG
E-BASED SOLUTION
AL REMOTE CONTROL
nart devices smart
Wireless Signal
Wireless Signal

Deep Learning Model

Scarcity Issue of Training Data

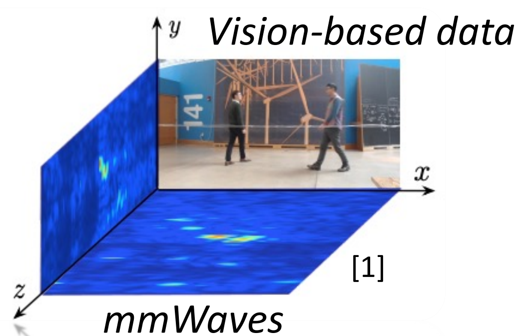
Quality Label Collection

Data-Modalities

User-Engagement

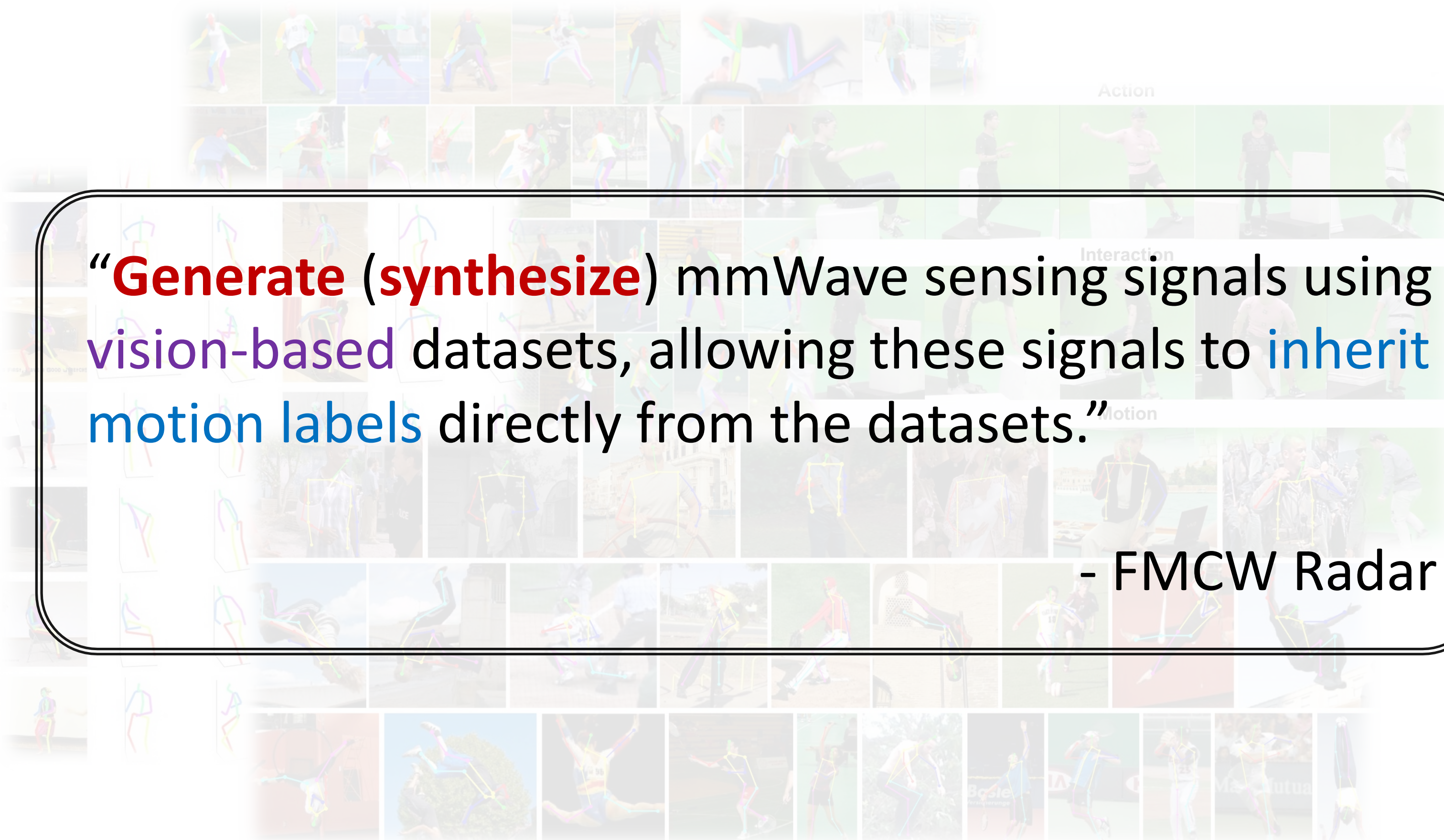
- **Expensive** devices
- **Multi-modality** data
- **Over** engagement

Vicon, OptiTrack, etc.



[1] Through-Wall Human Pose Estimation Using Radio Signals, in CVPR 2018.

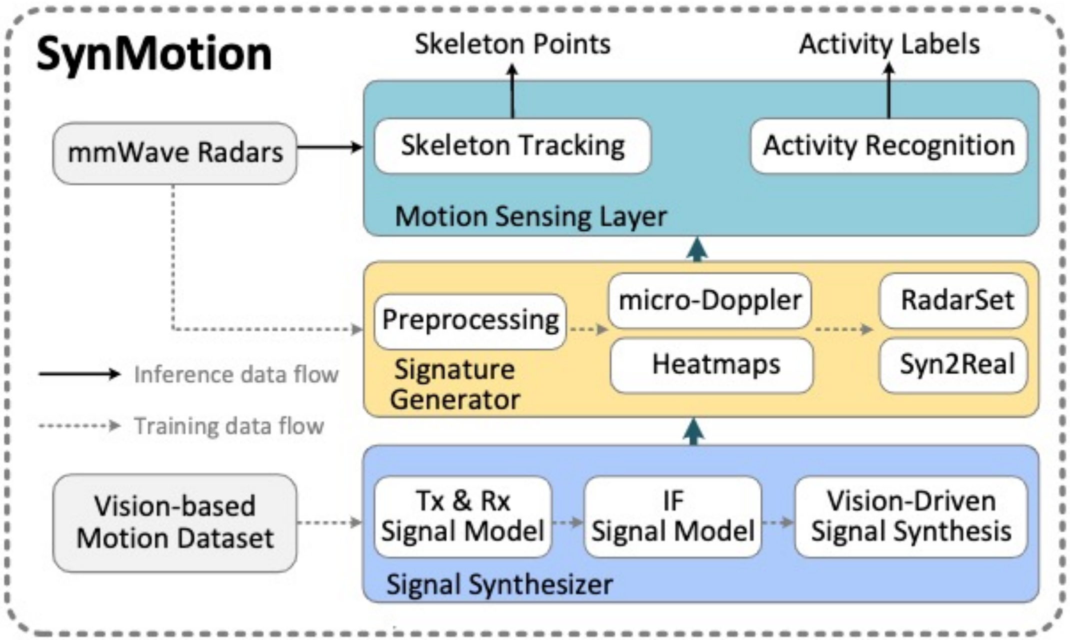
Key Idea of Our Solution



"**Generate** (**synthesize**) mmWave sensing signals using vision-based datasets, allowing these signals to inherit motion labels directly from the datasets."

- FMCW Radar

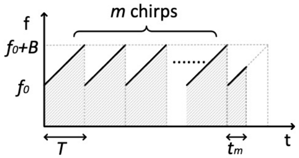
Our Solution – SynMotion

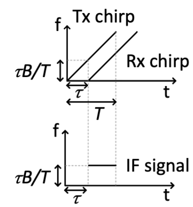


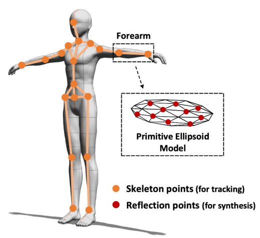
- **Module-3**: sensing services
- **Module-2**: sensing signatures
- **Module-1**: signal synthesis

Module-1: Signal Synthesis

- Signal synthesis pipeline







1. Transmitted FMCW Signal → 2. Reflected & Received Signal → 3. Intermediate Frequency (IF) → 4. Reflections from Body

$$S(t) = \sum_{k\in\mathcal{K}} \sum_{i=1}^{n} S_{IF}^{i}(t),$$

$s.t.$ $\quad$ *Tx and Rx signals are not blocked by body,*

$\sigma \in \mathcal{H}(ellipsoid),$

Module-1: Signal Synthesis

- Signal synthesis pipeline

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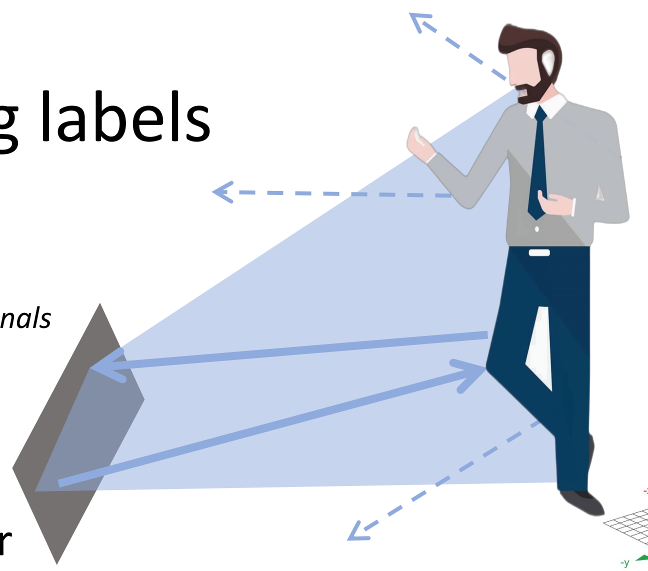
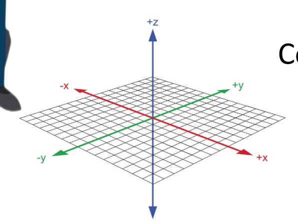
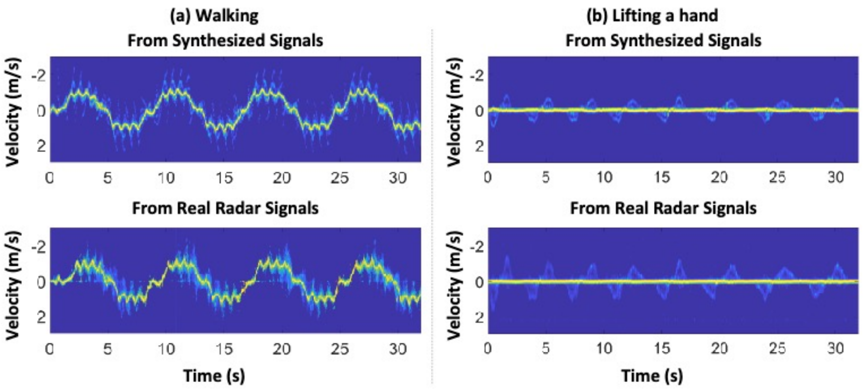
- Inheriting labels

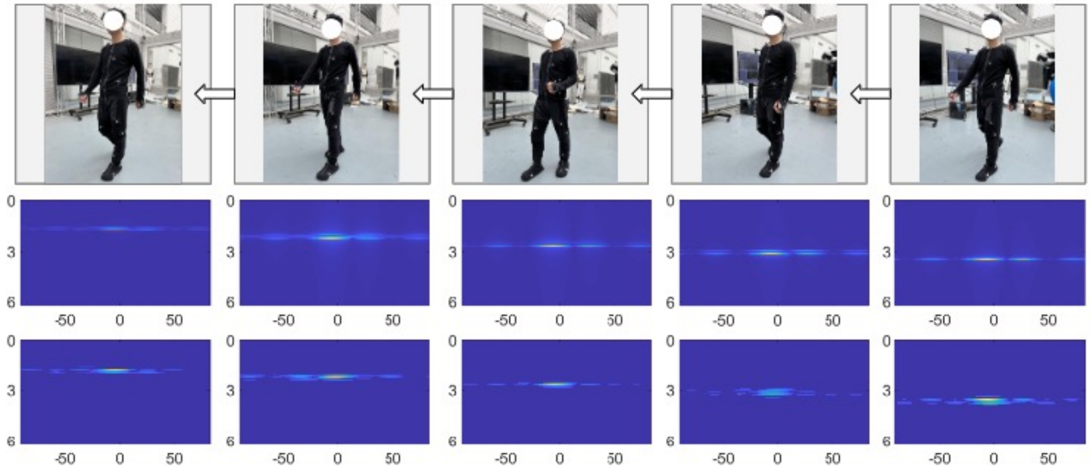




Module-2: Sensing Signatures

- Popular signatures
  - Micro-Doppler spectrum
    - Activity recognition
  - Heat map
    - Skeleton tracking





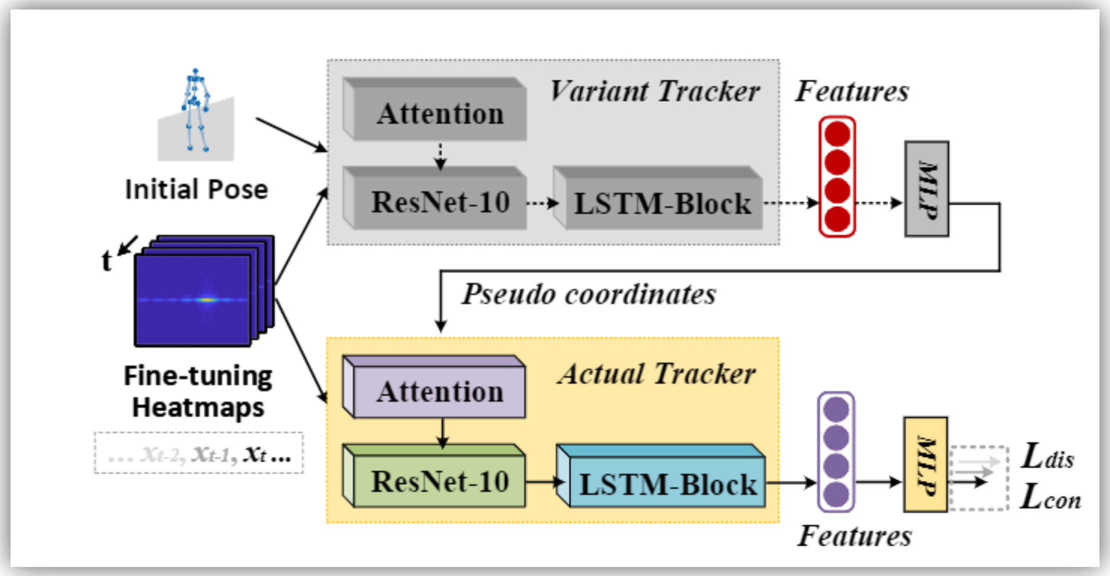
from **synthesized** signals

from **real** signals

Module-3: Compensation

Synthetic-to-Real Problem

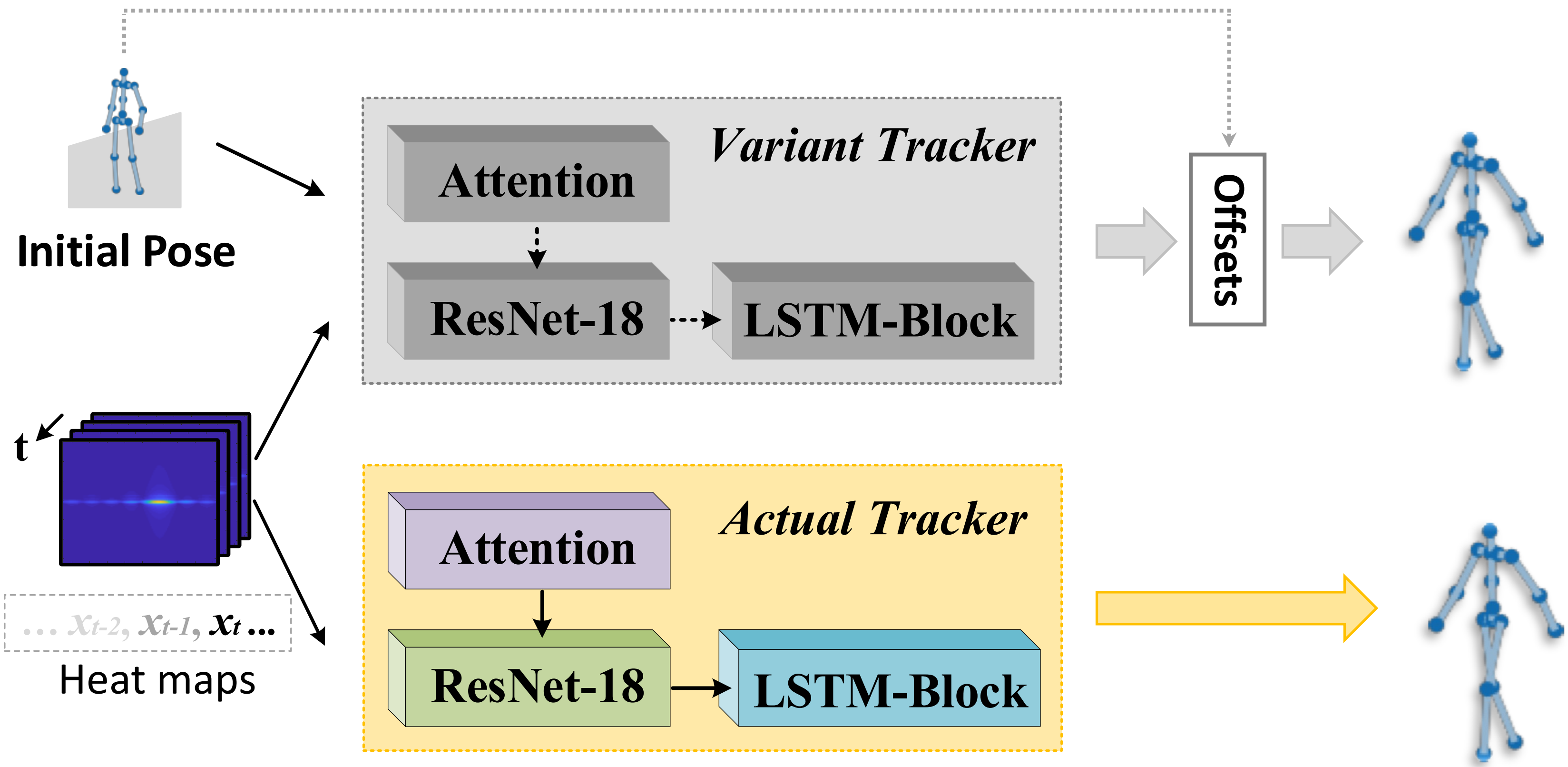
- **Fine-tuning** (with labeled data)



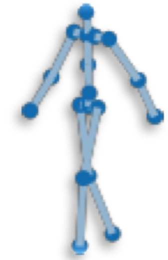
Training Framework

- Variant tracker & actual tracker
- Three training steps

Two Trackers



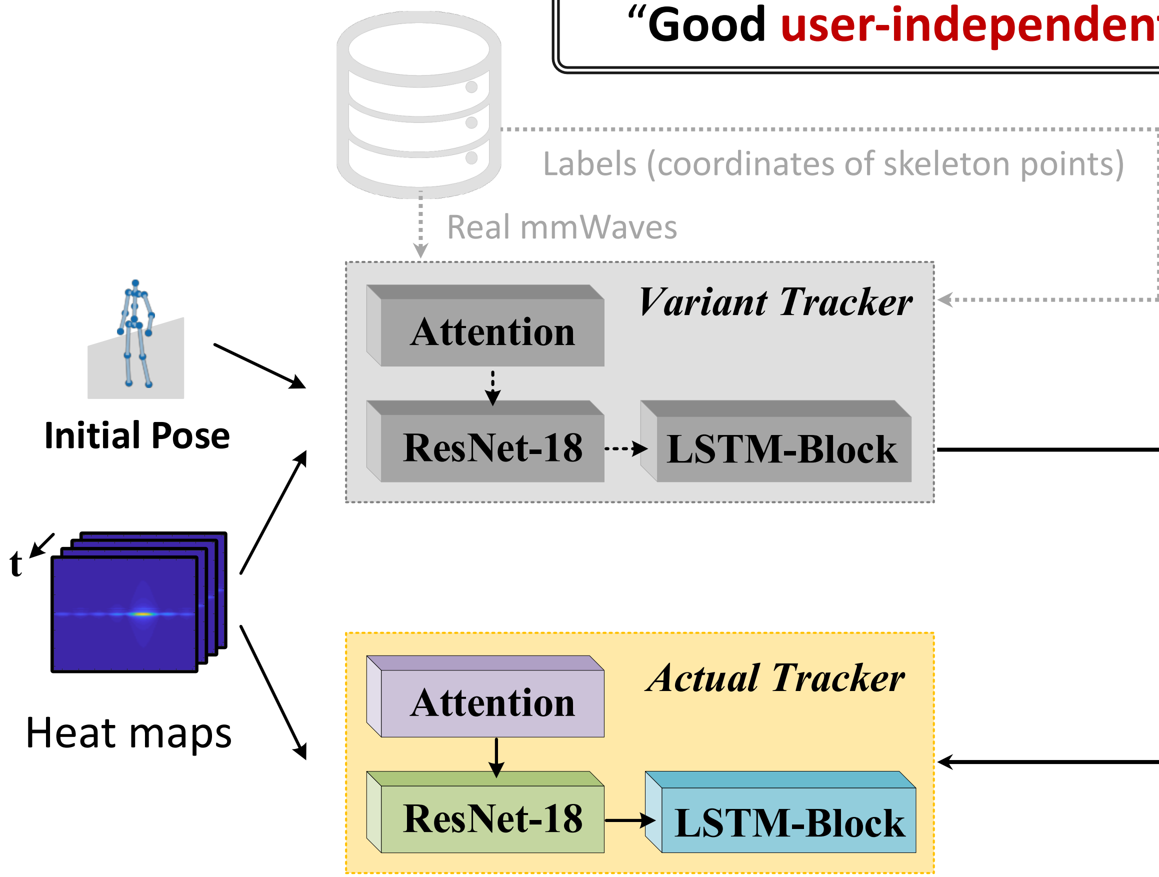
Two Trackers

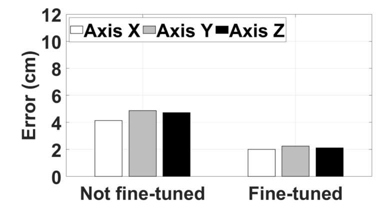


- Body **shape** ✓
- Skeleton **movement**

Three Training Steps

“Good user-independent feature”





Pseudo ground truth
(estimated coordinates)

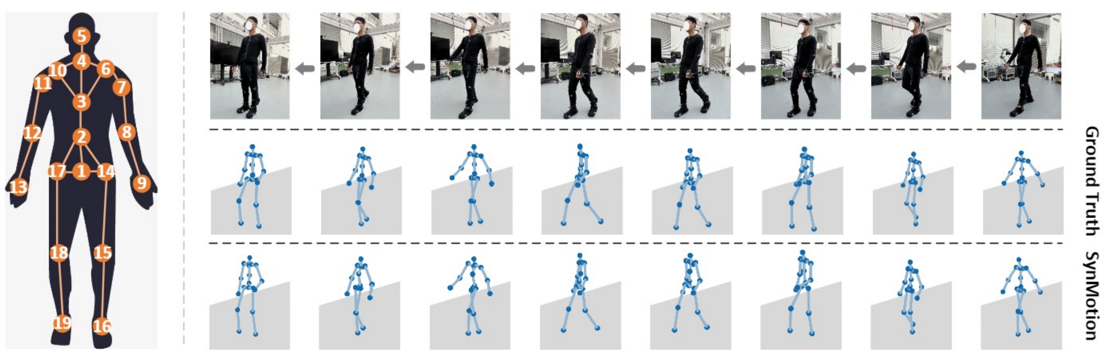
- **Step 1**: train both trackers using synthesized signals
- **Step 2**: fine-tune variant tracker
- **Step 3**: fine-tune actual tracker

Evaluation

- **Devices**
  - TI IWR1443BOOST radar
  - OptiTrack
- **Datesets**
  - Our dataset
    - Group-a): 10 users
    - Group-b): 10 users
  - Public datasets
    - NTU RGB+D
    - CMU MoCap

Evaluation

Skeleton Points	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Average
Axis X	1.9	2.0	2.0	2.2	2.8	2.2	2.5	2.6	5.3	2.2	2.5	3.5	5.3	2.0	2.6	2.6	2.1	4.3	3.4	2.9
Axis Y	1.4	1.4	1.6	1.5	1.8	1.5	1.8	4.1	4.5	1.6	2.3	4.7	5.9	1.4	0.6	0.6	1.4	2.1	2.5	2.5
Axis Z	2.7	2.7	2.9	3.2	3.5	3.1	3.1	3.7	4.8	3.2	3.3	4.4	4.2	2.6	2.7	2.7	2.7	2.6	2.9	3.2
Overall	4.5	4.6	4.8	5.2	6.0	5.1	5.4	7.0	8.8	5.2	5.8	7.9	9.1	4.6	4.3	4.3	4.6	6.5	6.4	5.8



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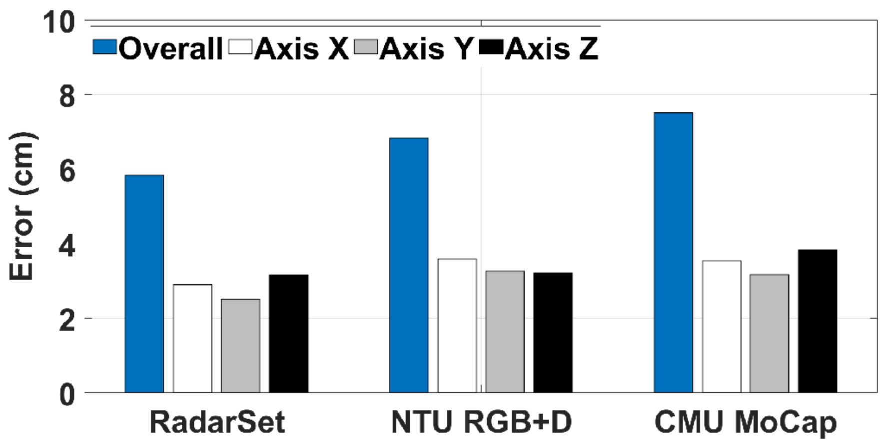
- **SynMotion**
  - Overall error: 5.8 cm
- **RF-Pose3D [2]**
  - Overall error: 5.3 cm

[2] RF-Based 3D Skeletons, in ACM SIGCOMM, 2018

Evaluation

- Different datasets



- **Our dataset**
  - Per-axis error: 2.5 – 3.2 cm
- **NTU RGB+D**
  - Per-axis error: 3.2 – 3.6 cm
- **CMU MoCap**
  - Per-axis error: 3.2 – 3.8 cm

Conclusion 1, 2, 3

1. **One goal:**
    - Solve the scarcity issue of training data

2. **Two aspects of significance:**
    - Bootstrap mmWave sensing at low cost
    - Enhance interpretability of mmWave sensing

3. **Three modules:**
    - Signal synthesis
    - Sensing signatures
    - Synthetic-to-real training

Thank you
Q&A